Value of Aggregators

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Abstract

Aggregators are facing increased scrutiny by regulatory authorities, suggesting these sites have considerable market power. On the other extreme, firms are bypassing aggregators, choosing instead to sell directly to consumers. This raises the question as to which party has more market power: the aggregator or the individual firm. Focusing on the airline industry, we investigate who benefits the most in the airline-aggregator relationship. Specifically, we ask what would happen to airline and aggregator site visits and purchases in the absence of a comprehensive aggregator. We first explore consumers' search patterns on Southwest, an airline that has never been part of any aggregator. In a descriptive exercise, we find that consumers who book on Southwest are the least likely to visit aggregator sites. Second, we use the 2011 American dispute with Orbitz as an exogenous event, which led to American fares no longer being displayed on Orbitz for five months. We use this dispute to identify who was hurt the most – the aggregator or the airline - in the months following the dispute. Our findings indicate the aggregator loses the most when it is not comprehensive.

1 Introduction

Search aggregators, such as Google, Kayak, and Expedia, improve consumers' search experience by providing a quick and comprehensive view of all available options, resulting in better matches between consumers and products. Aggregators also help consumers discover new or unfamiliar products (e.g., a niche hotel, a new airline route). However, aggregators are facing increased scrutiny by regulatory authorities who fear that many firms are at the mercy of aggregators and their ranking algorithms[1]. If aggregators have more market power, a firm that is not part of an aggregator risks not being discovered by consumers. On the other extreme, many firms are bypassing aggregators completely, choosing instead to sell directly to consumers. This behavior might arise if firms have more market power and prefer to not be part of an aggregator that makes price comparison easy, increasing price competition and eroding brand value. Who has the upper hand in the firm-aggregator relationship is an increasingly relevant question for regulatory authorities.

Focusing on the airline industry, this paper investigates who benefits the most in the airline-aggregator relationship. Although aggregators help airlines by enabling consumers to find their best match, aggregators need the presence of more airlines to be comprehensive and hence useful to consumers. With airlines questioning the value of search aggregators, we ask what would happen to airline and aggregator site visits and purchases in the absence of a comprehensive aggregator. Enabled by digital technology, airlines are beginning to bypass online ticket aggregators and global distribution systems, preferring to sell directly to consumers. For example, Southwest sells its tickets only on southwest.com and is not available for purchase on any flight aggregator. Disputes between aggregators and airlines over fees have also been on the rise: American pulled its listings from Orbitz in 2011 following a dispute over distribution fees on flight-reservation systems; Delta, in 2013, delisted its flights from several online travel websites.

Using detailed browsing data from comScore, we first document that most consumers use aggregators before making a final purchase at an airline's website. Southwest, which sells tickets only directly through its website, sees an exception to this general behavior: its users are the least likely to visit aggregators. We also document that loyalty to airlines is more common than to aggregators: nearly 52% of users browse only one airline, while most users use multiple aggregators in their searches.

We next turn to identifying a causal link between aggregator search and airline visits. To do so, we take advantage of a dispute between American airlines and Orbitz surrounding the

[1]For example, the EU commission is drafting regulation aimed at increasing transparency as to how search engines, e-commerce sites, and app stores rank their results and why they delist some services (Reuters 2018).

payment of distribution fees. Because of this dispute, American tickets were not displayed on Orbitz for nearly 5 months from December 21, 2010 - June 2, 2011. The dispute created a clear shift in the choice set available to consumers visiting Orbitz, with the timing being driven entirely by the contract renegotiation deadline, thus creating a quasi-experimental setting. Expedia delisted American's flights for a shorter 3 month period from January 1, 2011-April 5, 2011. A *Time* (2011) article reported, "In bypassing the online travel agents, American saves on distribution costs, but can also raise its ticket prices more easily, since its fares won't be displayed directly beside those of its competitors."

We find that during the dispute period, the aggregator was negatively impacted in both its site visits and purchases. Site visits at Orbitz and Expedia dropped by nearly 10% and purchases by 2%. On the other hand, American did not experience a significant change in its site visits or purchases. Moreover, we find that consumers living near airports where American is the most important airline continued to use Orbitz and Expedia, perhaps because they knew about American's offerings and used Orbitz and Expedia to learn about other competing offerings. However, consumers near airports where another airline (e.g., United) is the most important, and American is present, were more likely to leave Orbitz and Expedia during the dispute period, likely because without American's information, these sites were not as useful. This dimension of consumer heterogeneity suggests that when an aggregator is not comprehensive, its usefulness drops.

Next, we test two main predictions suggested by the theoretical and empirical literature related to the degree of manufacturer competition and customer loyalty. On competition, the literature suggests manufacturer competition should make for higher retailer market power (O'Brien and Shaffer 1997, Kadiyali et al 2000). Utilizing the variation in the localized nature of airline competition across airports, we find empirical support for this theory. On loyalty, the literature suggests loyalty to the manufacturer can relieve competition thus giving the manufacturer more power. Ailawadi et al (2010) highlight the theoretical work around this. Correspondingly, we expect loyalty to retailers gives the retailer more power. We indeed find the biggest decline in usage of Orbitz and Expedia is among users who are least loyal, i.e., who use multiple aggregators. This analysis provides further evidence of aggregators' limited market power in this industry.

We also investigate supply side responses such as pricing and advertising changes during the dispute period. We find some evidence suggesting competing aggregators such as Priceline might have increased their Internet ad expenditure. We therefore further control for ad expenditure in our demand regressions, and find that our results are robust. The possibility that competitors might respond further highlights the need for the aggregator to be comprehensive and the dependence of the aggregator on the firm.

Our results have implications for regulatory authorities and policy makers, and suggest aggregators and search engines do not necessarily always have substantial market power. The relationship between firms and aggregators can be industry-specific and needs to be evaluated on a case-by-case basis. In our setting, where there are multiple aggregators which users can easily substitute between and relatively few airlines, we find the aggregator does not have much market power.

1.1 Contribution

Closely related to the incentives at work in this industry, Baye and Morgan (2001) theoretically show that in a homogeneous product market, an aggregator has incentives to gain full consumer participation but keep firm participation partial. This is because when all firms participate, prices drop to marginal costs, removing incentives for the firm to pay a fee to the aggregator or for the consumer to use the aggregator's site. The gatekeeper would rather have some firms not participate to encourage price dispersion. This perhaps can explain why Southwest is not part of an aggregator and advertises itself as a "low-cost" carrier. This can also explain why the disputes lasted only a few months and did not lead to a new equilibrium with airlines permanently absent from aggregators. Our goal is to empirically identify who benefits the most in the airline-aggregator relationship and identify how consumers react to the absence of a prominent airline from an aggregator.

The importance of aggregators has been empirically analyzed in the news industry (Athey et al. 2016, Chiou and Tucker 2017, Calzada and Gil 2016), where similar disputes have arisen between aggregators and news outlets. However, whereas news aggregators can act as complete substitutes to news outlets threatening the outlets' revenue stream, in our setting, the aggregator merely serves as an additional channel, with airlines still earning most of the revenue.

Closely related to this paper, Biltokach, Rupp and Pai (2017) use the American-Orbitz dispute to examine resulting airline fare and demand changes. In contrast, our paper focuses on the impact of the dispute on aggregators to understand who has more market power: airlines or aggregators. Our paper adds to their work by examining detailed browsing-level data to understand consumers' visitation behavior prior to purchase. We also utilize the variation in the degree of airline competition at various airports as well as individual-level differences in loyalty towards aggregators to examine heterogenous treatment effects and test various theoretical predictions.

Beyond online domains, aggregators are ubiquitous in the retail channel. The question of who has more market power in the retailer-manufacturer relationship has received a lot of empirical attention in the marketing literature. Ailawadi et al. (2010), in their review paper, highlight the divergent results reported in empirical work. For example, Villas-Boas and Zhao 2005; Draganska et al. 2010 find evidence of manufacturer power while Kadiyali et al. (2000) find evidence of retailer power. In most of these settings, researchers do not observe wholesale prices and/or marginal costs, which makes inference rely on certain modeling assumptions, e.g., assuming a specific competitive structure such as monopolistic retailers. Even when wholesale prices and markups are observed, the counterfactual bargaining outcome is not observed, i.e., what would happen were the manufacturer not present in the retailer's assortment? Therefore, one cannot separately distinguish between manufacturers strong bargaining skills and retailers poor outside options (Noton and Elberg 2018 elaborate on this). One needs to observe entry/exit of manufacturers and episodes of disagreements between the retailer and manufacturer to rightly infer who has more power. We contribute to this literature by providing a setting to infer market power using the exogenous exit of an airline (manufacturer) from an aggregator (retailer) for a finite amount of time.

2 Institutional Details

Understanding the reason for the disputes between airlines and aggregators requires an understanding of the way tickets are distributed and the various revenue models in place.

Revenue sources of OTAs and meta-search sites

Airline search aggregators consist of online travel agencies (OTAs) such as Orbitz and Expedia, and meta-search sites such as Kayak. When a consumer purchases a ticket from an OTA, the OTA earns a commission from the airline. If a consumer uses an OTA to find her best match and then goes on to the airline website to buy her ticket, the OTA does not get paid. Meta-search sites, on the other hand, earn revenues through referral fees from directing consumers to the airline's website, irrespective of whether a purchase is made.

Both OTAs and meta-search sites also earn revenues from ad placements. Booking fees were an additional source of revenue for the OTAs, eliminated prior to the timespan we study in our paper: Priceline and Expedia's Hotwire stopped charging fees in 2007, and Travelocity and Orbitz eliminated fees in 2009. Recently, some of the aggregators have reinstated these booking fees. Finally, OTAs earn revenue from hotel and vacation packages. For Orbitz, in 2010, the revenue split was 36% from Air, 27% from Hotel, 15% from Vacation Packages, 7% from Media and Advertising and the remaining from Other (Orbitz 10K, 2010).

Distribution fees

All OTAs use global distribution systems (GDSs), which are flight-reservation systems. Every time a ticket is purchased through an OTA, the airline not only pays a commission to the OTA (~\$5), but also pays a fee to the GDS (~\$9). The GDS then passes approximately 50% of this fee to the OTA. To avoid paying the distribution fee, airlines have been trying to create their own reservation systems. Another reason for airlines to own their reservation systems is that GDSs do not have the capabilities to showcase add-on features such as upgrades. For these two reasons, American, at the time of its contract renewal in December 2010, wanted Orbitz to use its Direct Connect reservation system instead of relying on Sabre's GDS. Orbitz, however, resisted making the change, because it would mean the loss of nearly half of its revenues whenever an American ticket is booked.

2.1 Consumers' valuation of airlines and aggregators

In the absence of an aggregator, airline visits can decrease, increase, or stay the same: they could decrease if consumers are less likely to find the airline in the absence of the aggregator, they could increase if the value of visiting an additional airline is informative to the consumer, and they could stay the same if visiting additional sites adds no value or is too costly. Similarly, aggregator visits when the aggregator is not comprehensive can either decrease or stay the same.

Consumers typically visit both aggregators and airlines to learn about their best match value. Consumers can gain partial information about airlines by visiting an aggregator, but to learn additional airline-specific details, the consumer has to visit the airline. In addition, aggregators help consumers find their match by increasing their probability of discovering an airline.

Consider a path where a consumer visits the aggregator and one airline before making her purchase. We now delineate cases where in the absence of an aggregator, airline visits stay the same, increase, or decrease.

1. Airline visits stay the same. This scenario would occur when the consumer knows about and continues to visit the first airline, but the information gain from another airline does not justify the additional visit.

2. Airline visits increase. Under this scenario, visiting an additional airline is informative to the consumer. Furthermore, she needs to be aware of the existence of this airline, i.e., the probability of discovery is greater than zero.

3. Airline visits decrease. Because the consumer's valuation of visiting the individual airline was high (she visited the airline when the aggregator was present), the only way this scenario would occur is if the probability of discovery drops to 0; that is without the aggregator, the consumer is unable to find her true match.

We now delineate cases where, when the aggregator is not comprehensive, aggregator visits can either decrease or stay the same. To simplify the illustration, we assume one airline decides to opt out of being included in the aggregator.

1. Aggregator visits stay the same. This scenario would occur if the absence of the airline does not change the information value drastically; that is it is still worth learning partial information about the remaining airlines.

2. Aggregator visits decrease. When the aggregator is not comprehensive, the partial information available at the aggregator is insufficient to justify the cost of a visit.

Therefore, the true impact of a firm's absence from an aggregator is an empirical one and depends on the context (e.g., the airline industry is likely to behave very differently from the hotel industry).

3 Data

To understand how consumers search and buy tickets online, we need detailed browsing data that track consumers' website visits across various domains. We use comScore's web behavior database, which consists of a sample of 50,000 internet users randomly chosen from a cross-section of more than 2 million internet users (comScore Database Manual). We supplement this dataset with the Airline Origin and Destination Survey (DB1B) from the Bureau of Transportation Statistics to get measures of demand and prices. The DB1B database is a 10% sample of airline tickets consisting of origin, operating carrier, number of passengers, and itinerary fare aggregated at the quarterly level every year. The data cover 37 airlines and over 500 airports. We also use the Nielsen Monitor-Plus media database to get measures of ad expenditure by brands across various types of media.

From the comScore database, we select those searches and transactions that pertain to airlines and aggregators. We select the top airlines, by passengers flown as reported in the DB1B survey, which have non-zero transactions in the comScore database. We further select those domains that have at least 10,000 visits (searches and transactions) across our panel: the cutoff is at 13,433 visits for Alaska Airlines, with the next popular domain being CheapAir with only 6,608 visits. Table 1 shows the included websites, the total number of search-related visits to each domain, and the number of transactions. We do not include Google Flights and Bing Travel because our data do not distinguish sub-domains, i.e., we cannot identify google.com/flights separately from google.com. Including all of Google's and Bing's searches would increase our datasize immensely without necessarily increasing the accuracy of our estimates. Moreover, Google Flights was launched in late 2011 and is therefore unlikely to interfere with the dispute period, which was in early 2011.

The number of unique users who visit airline or aggregator websites ranges from 26,000-30,000 across the years 2010-2012. comScore tracks the exact timestamp for when a particular website was visited. Each visit comprises a search session, and comScore tracks the duration spent, the number of pages viewed, and whether a transaction was made in that session. Table 2 summarizes these statistics across all users as well as conditional on those users who made a purchase. Furthermore, user demographics such as income, education, and zipcode are present in the dataset.

A majority of visits to airline/aggregator websites (~ 55%) occur in the month before purchase, with 80% occurring within 4 months of the purchase date. We assume that all of these visits and searches are related to the final purchased itinerary. In a robustness check, we verify our results, assuming only site visits one month prior to the last recorded event per user are relevant. Our dataset also includes those searches that did not result in a purchase. Of these, 35% visit a travel website once and never return over the course of the panel, 12% search over the course of a month, and the remainder search repeatedly for more than a month but never purchase. Note we do not know if these visits are directed searches toward a purchase, or random visits.

Table 1: Total Number of Searches and Transactions on Travel Domains, 2010-2012

Airlines			Aggregators		
Domain	Searches	Transactions	Domain	Searches	Transactions
aa.com	57,951	1,435	cheapflights.com	17,364	-
airtran.com	22,256	889	cheapoair.com	63,473	-
alaskaair.com	12,740	693	expedia.com	194,459	1,878
continental.com	23,772	629	hotwire.com	49,894	288
delta.com	67,154	1,549	kayak.com	58,850	-
jetblue.com	37,413	764	orbitz.com	97,961	1,439
southwest.com	100,730	6,705	priceline.com	107,911	1,631
united.com	32,194	821	travelocity.com	70,586	963
usairways.com	23,666	827			

Table 2: Descriptive Statistics: comScore data, Travel Domains 2010-2012

	All searches		Conditional on purchase	
	Median	Mean	Median	Mean
Number of websites visited	4.00	10.68	9.00	16.57
Time spent on search (minutes)	21.00	71.62	58.00	120.30
Total pages viewed	22.00	69.16	56.00	113.20
Transactions	0	0.25	1	2.01
Number of unique users	82,886		10,232	
Total purchases			20,511	

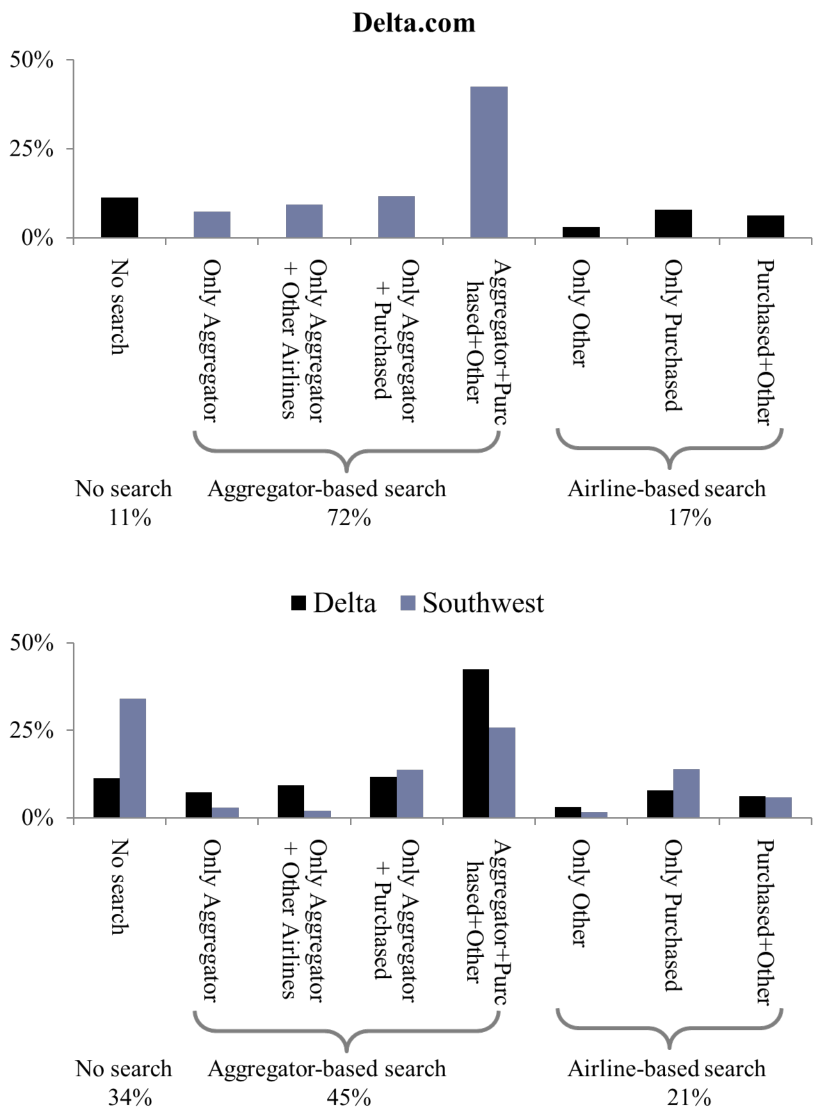
3.1 Descriptive Evidence: Search patterns on aggregators and domains

For every purchased ticket, we identify how many visits were made to an aggregator, the purchased airline, and any non-purchased airline, prior to making a ticket purchase. Figure 1 highlights all possible browsing patterns for a typical airline, using Delta as an example. We see that for a typical airline, the most common search pattern involves visits to all three types of sites: aggregators, the purchased airline, and other airlines. 72% of all searches involves the use of aggregators at least once. The only airline in contrast to this search pattern is Southwest, which does not participate with any aggregator, where the most common pattern is an user going to Southwest and making a purchase directly without any search. Only 45% of searches use aggregators. Southwest's search pattern suggests that not being part of an aggregator does not necessarily hurt the airline. Note that these patterns could result if Southwest's customers are very different from other airlines' customers, and also if Southwest allocates marketing resources specifically recognizing it is not part of an aggregator. Moreover, we do not observe the counterfactual of what would happen if Southwest were part of an aggregator. Our empirical exercise in Section 4 will address this issue directly.

Next, we turn to identifying when in the search history aggregators were visited relative to the purchased airline. If consumers are fairly well informed about their destination airline and are merely browsing other websites before making a purchase, we should see the purchased airline being visited earlier. On the other hand, if a consumer searches an aggregator first and then subsequent airlines, we should see aggregators being visited earlier. To study this pattern, we document for all purchased tickets on an airline's domain, the rank order of the purchased airline and of any aggregator. Figure 2 plots these ranks. We observe that for most airlines, the aggregator is visited first and then the purchased airline. Exceptions to this pattern are Southwest and Jetblue, the low-cost airlines, where consumers are more likely to visit the purchased airline first.

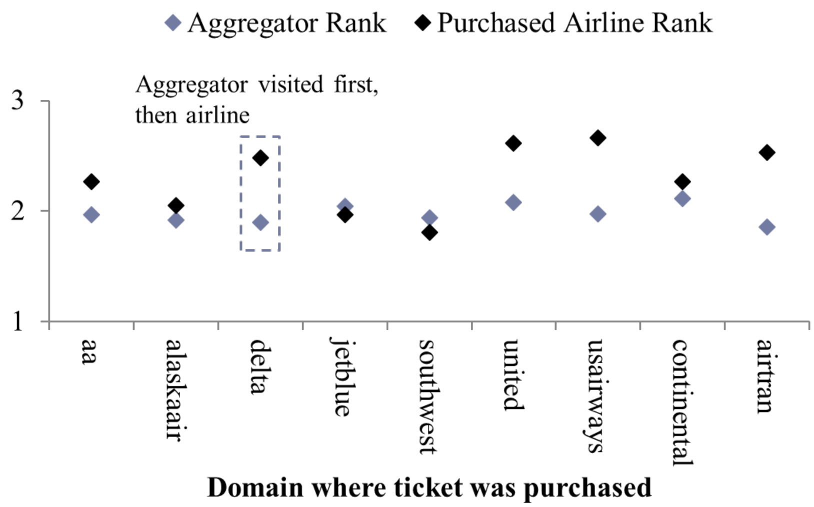
Last, we document a rough measure of the relative market power of aggregators and airlines using consumers' browsing history. We identify the number of users who browse only a single aggregator, 2-3 different aggregators, or multiple aggregators. We find that the split is roughly a third in each group, i.e. 36% users browse a single aggregator, 32% browse 2-3 aggregators and 32% browse more than three aggregators. We do the same for airlines. In stark contrast, loyalty to airline domains is much higher. Over 50% of users browse only a single airline, 34% browse 2-3 airlines and the rest browse more than three airlines. Table 3 provides these summary statistics indicating that competition among aggregators is fairly high. Next, we condition on users who browsed a given aggregator atleast once, and repeat the exercise. Table 4 shows the split into each of these three categories, users very rarely browse only one aggregator (7%-21%) with Expedia exhibiting the strongest loyalty. Most users browse multiple aggregators. Repeating this exercise for airlines, and consistent with the finding in Table 3, users exhibit more loyalty towards airlines with 17%-38% browsing only 1 airline with Southwest exhibiting the strongest loyalty.

Although these patterns indicate the extent to which customers use aggregators to find their ultimate match, and show that being absent from an aggregator is not necessarily harmful to an airline, they do not establish any causal effect. To do so, we turn to the American-Orbitz dispute that resulted in American being unavailable on Orbitz's website for over 5 months.



Note: No Search indicates a user visited the site and purchased her ticket in that session. Only Purchased indicates the user visited the purchased airline's site a few times but purchased her ticket after a few such visits. Note these two could be grouped into one category because they both involve only the destination airline.

Figure 1: Southwest users go directly to southwest.com; all other airlines search an aggregator before making a purchase



Note: Rank averaged across users, and is determined by order of search per user. As an example, if a user visits an aggregator first and the airline where the ticket was purchased third, the aggregator's rank=1 and the purchased airline's rank=3.

Figure 2: Consumers start their search at an aggregator, except Southwest and Jetblue users

Table 3: Percent of user who browse few vs. multiple aggregators and airlines

Browse only	% users	Browse only	% users
1 aggregator	36%	1 airline	52%
2-3 aggregators	32%	2-3 airlines	34%
>=4 aggregators	32%	>=4 airlines	14%

Table 4: Of those who browse an aggregator atleast once, how many visit only that aggregator vs. multiple

Browse only	Orbitz	Expedia	Priceline	Travelocity	Kayak	Hotwire	Cheapoair	Cheapflights
1 aggregator	9%	21%	12%	11%	8%	7%	9%	7%
2-3 aggregators	28%	33%	28%	26%	20%	23%	22%	20%
>=4 aggregators	63%	45%	59%	63%	72%	69%	69%	73%

4 Empirical Evidence

We use the American-Orbitz dispute to identify the effect of the absence of a major airline from a popular aggregator. We examine both search and purchase behavior during this dispute period and compare it with the same period one year before and one year after. Figure 3 plots the monthly site visits at Orbitz and American as a proportion of visits to all travel websites. Orbitz appears to face a decline in site visits during the dispute period (grey shaded area) in the year 2011, compared to the control periods in 2010 and 2012.

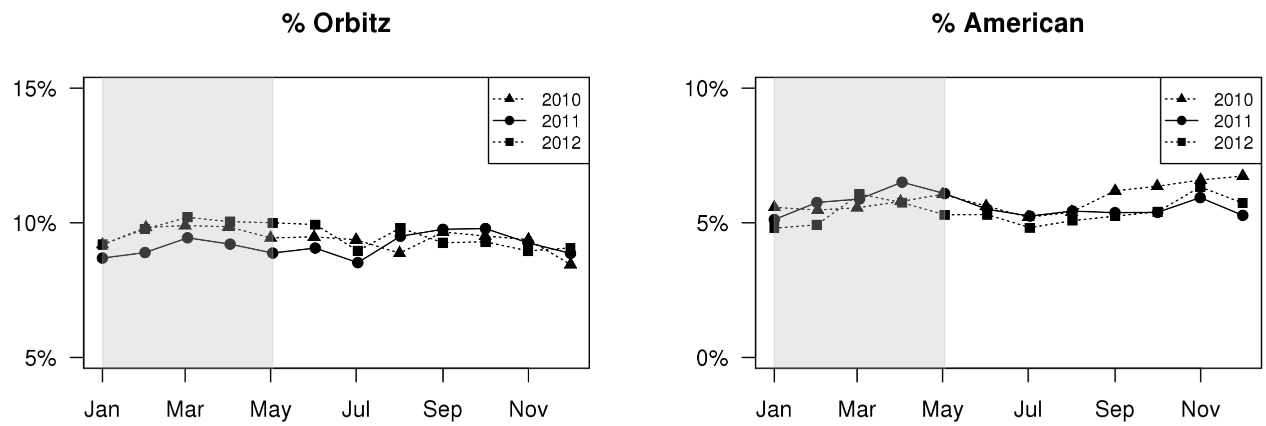
American does not seem to be impacted. We next turn to the individual level, where for each consumer's itinerary, we construct[2] three dependent variables:

sites: the number of times a domain's website was visited in a month,

pages: the number of pages viewed at the domain's website that month, and

durn: the duration spent on the website that month.

We focus on only those months when an individual engaged in a travel-related search. If there is a month in which no travel website is visited by an individual, we do not include that individual-month in the data[3]. We first present how the impacted domains - aa.com, orbitz.com, and expedia.com - perform relative to their competitors and the control period. We then explore which type of consumer the dispute had a greater impact on.



Note: The grey shaded area represents the dispute months, January-May. Year 2011 corresponds to the year of the dispute, 2010 and 2012 serve as control years.

Figure 3: Site visits at Orbitz and American as a percent of site visits at all travel websites

4.1 Search intensity relative to competitors and control period

For each of the impacted domains, we evaluate the search intensity during the dispute period relative to the same period in the past (2010) and future (2012) years. As controls, we choose the same months when the dispute occurred: January-May but in the previous year and the

[2]When there is no final purchase, we group all the non-purchase-related searches into one itinerary.

[3]In a robustness check, we expand the data to include those months when no travel-related search was performed: this approach allows total searches to increase/decrease. When an individual did not search or visit any given domain in a month, the dependent variables take on the value 0. Doing so allows for the scenario where consumers increase their total search volume at a given domain when they can no longer find aa.com on an aggregator. The results are fairly similar in this specification but are quantitatively smaller in magnitude because of the large number of additional 0's.

future year: 2010 and 2012. We focus on the same set of months as the dispute period to hold constant any seasonality patterns that might exist. We conduct a pooled (treating 2010 and 2012 equally) regression. Results are robust to an un-pooled regression (treating the two years separately). To rule out any industry-wide trend (e.g., delta.com, priceline.com might also be impacted), we further include competitors and measure the change relative not only to the control periods, but also to the competitors. Note that doing so measures the net competitive effect of the dispute period on the impacted domains. In other words, if consumers shift their searches from Orbitz to Priceline during the dispute period, we are measuring the decrease in Orbitz relative to the increase in Priceline, relative to the baseline years. We address this potential contamination of the control group in Section 4.1.1.

For each of the impacted domains, we estimate the following regression separately:

$$\begin{aligned} y_{ijt} = {} & \beta_0 D_t + \beta_1 D_t \times Disp_Y \\ & + \beta_0^F D_t \times Focal_j + \beta_1^F D_t \times Disp_Y \times Focal_j \\ & + \alpha_{tY} + \alpha_{tY}^F Focal_j + \alpha_i + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where i is the individual, j is the domain, and t is time in months. Here, y_{ijt} is the dependent variable *sites*, *durn* and *pages*, $D_t = 1$ if t is between January and May, the months relevant to the dispute period in either the treated or untreated years, $Disp_Y = 1$ if the months correspond to the year the dispute occurred (2011). $Focal_j$ is an indicator that equals 1 if travel domain j is the impacted domain, i.e., American, Orbitz, or Expedia. β_0 and β_1 capture the average estimate of all travel websites visited during the control and dispute periods respectively (relative to the estimates in the rest of the year), β_0^F and β_1^F capture the additional change specific to the impacted domain's website in the control and dispute periods respectively. β_1^F is the treatment effect of the dispute period. α_{tY} is the year fixed effect that controls for any year-specific trends in the industry, α_{tY}^F is the year fixed effect for the impacted domain that controls for any year-specific trends in that domain, and α_i is the individual fixed effect. Standard errors are clustered at the individual level.

The results, reported in Table 5, show both Orbitz and Expedia experience a significant decline in site visits and duration spent by users. Site visits decline by 0.036 for Orbitz and 0.049 for Expedia. To put these numbers in context, the average number of site visits per month at Orbitz is 0.38 which implies a 10% drop in site visits, an economically meaningful drop. We discuss the further implications of this drop in Section 4.4. The results also show an increase in site visits to aa.com. Figure 4 plots the increase/decrease in duration and site visits across all three websites.

Interestingly, we see a decrease in page views to aa.com and no significant change in page views on orbitz.com and expedia.com. To further investigate this pattern in page visits, we run a zero-inflated poisson regression which separates out the number of zero visits from those who visit, and conditional on those visiting, helps understand their behavior changes. Following Lambert (1992), we specify site visits follow the distribution:

$$y_{ijt} \sim \begin{cases} 0 & \text{with probability } p_{ijt} \\ Poisson\left(\lambda_{ijt}\right) & \text{with probability } 1 - p_{ijt} \end{cases} \tag{2}$$

where $\lambda_{ijt} = exp\left(\beta X\right)$. βX uses the same specification as equation 1. The portion that accounts for the excess zeros, p_{ijt}, is modeled using a logit model, such that $p_{ijt} = \frac{exp(\zeta X)}{1+exp(\zeta X)}$ where ζX is the same specification used in equation 1. Table 6 presents the results of this regression. From this table, we see that aa.com sees more visitors: the coefficient for the zero-inflated part of the regression is negative and significant indicating a drop in number of zero-visits. However, conditional on a visit, aa.com sees fewer page views. We believe this occurs because of the selection of consumers visiting the site during the dispute period. More people visit aa.com during the dispute, but might not find a good match and hence do not browse as many pages, as consumers who come there with greater certainty of booking. Similarly, for Orbitz and Expedia, fewer people visit the site but those who visit are a select group who care more about other airlines information and hence browse more pages.

Table 5: Searches on impacted domains, relative to competitors and pooled control period

(1) sites		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.022	7.22	0.021	6.87	0.018	6.30
Jan-May X Dispute	β_1	-0.009	-1.87	-0.006	-1.21	-0.005	-1.08
Jan-May X Focal	β_0^F	-0.006	-0.81	0.027	3.06	0.067	5.60
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.023**	**1.90**	**-0.036**	**-2.18**	**-0.049**	**-2.48**

(2) duration		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.186	6.87	0.173	6.63	0.135	5.29
Jan-May X Dispute	β_1	-0.054	-1.22	-0.033	-0.75	-0.024	-0.57
Jan-May X Focal	β_0^F	-0.034	-0.40	0.194	2.24	0.836	7.74
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.090**	**0.59**	**-0.272**	**-2.17**	**-0.417**	**-2.45**

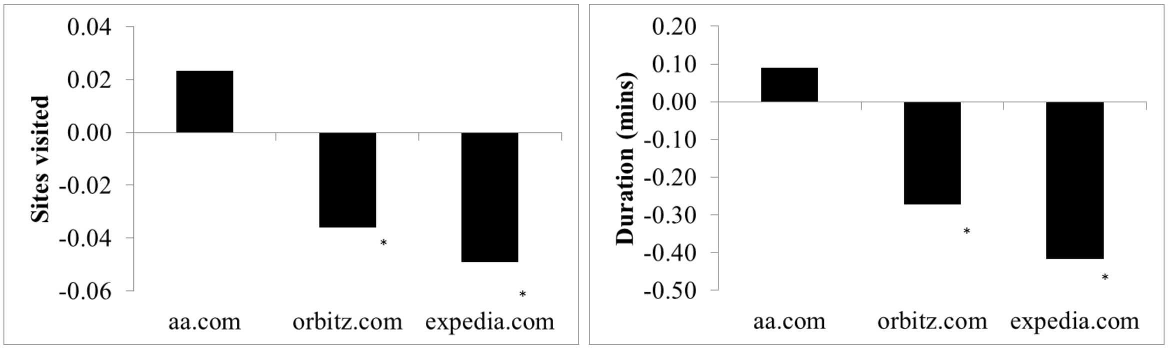
(3) pages		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.228	8.39	0.246	8.97	0.207	7.69
Jan-May X Dispute	β_1	-0.095	-1.92	-0.124	-2.43	-0.115	-2.28
Jan-May X Focal	β_0^F	0.407	3.51	0.107	1.49	0.762	8.07
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.428**	**-1.94**	**0.070**	**0.62**	**-0.085**	**-0.57**
N obs	4,389,417						
N id	82,886						
Fixed effects	id, year, year X focal						
Cluster	id						

Note: Tables present diff-in-diff analyses using all competitors as controls for each of the three dependant variables (1) sites, (2) duration and (3) pages. Each table presents 3 separate regressions run for each of the impacted domains, aa.com, orbitz.com and expedia.com. Jan-May is an indicator for the five months January-May, Dispute is an indicator for the year of the dispute 2011, Focal is an indicator for the impacted domain $\boldsymbol{\beta_1^F}$ is the relevant treatment effect.

Table 6: Diff-in-diff analysis using Zero-inflated poisson regression

(1) pages		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.042	3.70	0.064	5.46	0.047	3.75
Jan-May X Dispute	β_1	-0.030	-1.34	-0.066	-2.83	-0.062	-2.50
Jan-May X Domain	β_0^F	0.151	3.43	-0.094	-3.46	0.048	2.34
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**-0.278**	**-2.82**	**0.197**	**3.86**	**0.110**	**2.72**
Zero-Inflate							
Jan-May	ζ_0	-0.049	-9.51	-0.036	-7.02	-0.036	-6.44
Jan-May X Dispute	ζ_1	0.054	5.94	0.032	3.62	0.042	4.33
Jan-May X Domain	ζ_0^F	0.042	2.46	-0.134	-11.14	-0.101	-9.23
Jan-May X Dispute X Domain	$\boldsymbol{\zeta_1^F}$	**-0.171**	**-5.97**	**0.149**	**7.01**	**0.033**	**1.72**
(2) sites		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.009	0.60	0.018	1.31	0.005	0.34
Jan-May X Dispute	β_1	-0.014	-0.58	-0.025	-1.08	-0.010	-0.42
Jan-May X Domain	β_0^F	0.018	0.42	-0.095	-2.69	0.016	0.67
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**-0.084**	**-1.08**	**0.070**	**0.95**	**-0.039**	**-0.92**
Zero-Inflate							
Jan-May	ζ_0	-0.047	-5.34	-0.027	-3.26	-0.035	-3.84
Jan-May X Dispute	ζ_1	0.049	3.28	0.020	1.47	0.039	2.59
Jan-May X Domain	ζ_0^F	0.050	2.00	-0.205	-8.15	-0.113	-4.71
Jan-May X Dispute X Domain	$\boldsymbol{\zeta_1^F}$	**-0.216**	**-4.61**	**0.205**	**4.05**	**0.012**	**0.29**
N	4,389,417						
N obs	82,886						
Cluster	machine_id						

Note: Tables present diff-in-diff analyses using zero-inflated poisson regression. Each table presents 3 separate regressions run for each of the impacted domains, aa.com, orbitz.com and expedia.com, run for the dependant variable *pages*. The regressions for *sites* is also shown for comparison. Jan-May is an indicator for the five months January-May, Dispute is an indicator for the year of the dispute 2011, Focal is an indicator for the impacted domain. $\boldsymbol{\zeta_1^F}$ is the relevant treatment effect pertaining to a change in zero-visits. A negative $\boldsymbol{\zeta_1^F}$ implies fewer zero-visits.



Notes: * significant at the 95% level.

Figure 4: Duration spent and sites visited decreased for orbitz.com and expedia.com

4.1.1 Alternative Control Groups

We perform three additional exercises described below that do not directly rely on competitors as controls to establish the magnitude and the robustness of the effect.

Diff Analysis

First, we perform a simple diff analysis without using any competitors as controls. Assuming that the dispute period (Jan-May 2011) is comparable to the same period in the previous/post years (Jan-May 2010, 2012) in terms of seasonality, trends etc., this estimate tells us how much site visits changed in the year of the dispute relative to the same months in other years. This simple before-after analysis gives us one estimate of the lower bound on the impact of the dispute.

We run a regression specified by Equation 3, where δ_1 is the treatment effect of the dispute period. This regression includes only the impacted domains (competitor domains are excluded for this simple before-after analysis). For each of the dependant variables - sites, duration and pages - and for each of the impacted domains, we run a separate regression.

$$\begin{aligned} y_{ijt} &= \delta_0 D_t + \delta_1 D_t \times Disp_Y \\ &+ \alpha_{tY} + \alpha_i + \varepsilon_{ijt} \end{aligned} \tag{3}$$

where y_{ijt} is the dependant variable (sites, duration, pages visited on domain j) by individual i in month t. $D_t = 1$ if t is between January and May, the months relevant to the dispute period in either the treated or untreated years, $Disp_Y = 1$ if the months correspond to the year the dispute occurred (2011). α_{tY} and α_i are year and individual fixed-effects respectively.

Diff-in-Diff Analysis with Unlikely Competitors as Controls

Second, we estimate the same diff-in-diff regression (Equation 1) as before, but use competitors that are unlikely substitutes to the impacted domains. This helps rule out the fact that users would substitute to these domains during the dispute period. For each of the impacted domains, we measure the usage of the other domains to see which domains are least used together. For both Orbitz and Expedia, these domains are Cheapflights, Hotwire, Kayak and Cheapoair. Moreover, to your point in (iii) below, that not all these domains have airlines as their main focus, we restrict attention to Kayak and Cheapflights that focus on airlines (similar to Orbitz). Moreover, Kayak and Cheapflights are sufficiently different from Orbitz and Expedia in their business models: while users can book directly on Orbitz, Kayak and Cheapflights refer consumers to airline websites, earning a commission for each referral. All these taken together make Kayak and Cheapflights unlikely competitors, but at the same time good controls for any industry-wide trends. For American, these domains are Alaska Air and Airtran, which are rarely browsed by those users who browse American.

Diff-in-Diff Analysis with Lonely Planet as a Control

Third, we conduct a diff-in-diff analysis using visits to the website LonelyPlanet as a control. Per the entire review team's concerns and suggestions, we wanted to select a control site that is 1) unlikely to have spillovers from the treated firms (ruling out all websites where one can book airfare or hotels), but 2) still faces similar travel industry trends. Moreover, Lonely Planet is the only website where one cannot make a booking and is ranked among the top 15 travel websites[4].

Table 7 presents the results of the (1) simple before-after analysis, (2) diff-in-diff analysis using unlikely competitors as controls, and (3) diff-in-diff analysis using LonelyPlanet as a control. The results excluding the treated firms as well as the original results are also presented for comparison. The results show that across all three specifications, there was no significant change in users browsing behavior on aa.com, while Orbitz and Expedia see a significant decline in their browsing behavior during the dispute period. Moreover, the magnitude of the drop is identical: 0.03 site visits for Orbitz, 0.04 site visits for Expedia. For brevity we present results for only the dependant variable sites here. Tables 22-24 in Appendix A show the results for all three dependant variables: sites, duration and pages.

[4]http://www.ebizmba.com/articles/travel-websites

Table 7: Site visits to **aa.com** unchanged, to **orbitz.com** and **expedia.com** drop during the dispute period: Results robust to three different analyses

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
(1) before-after analysis							
Jan-May	δ_0	0.017	1.89	0.056	5.12	0.100	6.51
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.016**	**1.10**	**-0.035**	**-1.91**	**-0.037**	**-1.52**
N obs	258,201						
N id	82,886						
(2) diff-in-diff (unlikely competitors as controls)							
Jan-May	β_0	0.006	1.95	0.021	5.64	0.023	5.45
Jan-May X Dispute	β_1	0.009	1.47	-0.008	-1.24	-0.005	-0.64
Jan-May X Focal	β_0^F	0.003	0.41	0.025	2.76	0.063	5.17
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.006**	**0.44**	**-0.031**	**-1.82**	**-0.044**	**-2.15**
N obs	774,603						
N id	82,886						
(3) diff-in-diff (LonelyPlanet as control)							
Jan-May	β_0	0.010	3.56	0.013	3.84	0.015	3.51
Jan-May X Dispute	β_1	-0.004	-0.79	-0.001	-0.15	0.005	0.60
Jan-May X Focal	β_0^F	0.002	0.27	0.032	3.51	0.069	5.56
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.016**	**1.36**	**-0.038**	**-2.19**	**-0.048**	**-2.36**
N obs	525,300						
N id	83,991						
(3) diff-in-diff analysis (exclude treated websites from control)							
Jan-May	β_0	0.015	5.44	0.015	5.53	0.016	5.52
Jan-May X Dispute	β_1	-0.005	-1.25	-0.005	-1.16	-0.004	-0.97
Jan-May X Focal	β_0^F	0.000	0.03	0.031	3.48	0.069	5.70
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.018**	**1.47**	**-0.038**	**-2.24**	**-0.050**	**-2.50**
N obs	3,873,015						
N id	82,886						
(4) diff-in-diff analysis (original)							
Jan-May	β_0	0.022	7.22	0.021	6.87	0.018	6.30
Jan-May X Dispute	β_1	-0.009	-1.87	-0.006	-1.21	-0.005	-1.08
Jan-May X Focal	β_0^F	-0.006	-0.81	0.027	3.06	0.067	5.60
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.023**	**1.90**	**-0.036**	**-2.18**	**-0.049**	**-2.48**
N obs	4,389,417						
N id	82,886						
Fixed effects	machine_id, Year, Year X Focal						
Cluster	machine_id						

Note: (1) presents a before-after analysis for visits to the treated domains. (2) presents a diff-in-diff analysis comparing searches of those who browsed American/Orbitz/Expedia to those who browsed unlikely competitors: Alaska and AirTran for American, and Kayak and Cheapflights for Orbitz and Expedia. (3) presents a diff-in-diff analysis using visits to LonelyPlanet as a control. (4) presents a diff-in-diff analysis using all competitors (airlines and aggregators) except the treated firms as controls. (5) presents a diff-in-diff analysis using all competitors as controls. Each table presents 3 separate regressions run for the dependant variables sites. $\boldsymbol{\delta_1}$ in (1) and $\boldsymbol{\beta_1^F}$ in (2),(3), (4) and (5) are the relevant treatment effects.

4.1.2 Robustness Checks

In the main analysis, we assume all searches prior to the final visit/transaction are relevant. We now verify if our results are robust to using much shorter windows of search: 1 month and 2 months, i.e., we only use visits to travel domains up to 1 month and 2 months before the last visit. Tables 25 and 26 in Appendix B report the relevant estimates. We find that our results are robust to these specifications; specifically, we see Orbitz is negatively impacted (even more so) during the dispute period.

Next, we test if our results are robust to removing outliers in the data. The data contains instances when the number of pages viewed in a single session exceeds 100 and the duration spent exceeds 1 hour. In such instances a browsing window could have remained open for too long without active search. We therefore remove those sessions that exceed the 99th percentile in the data: more than 51 page views and 61 minutes for a single session. The results reported in Table 27 of Appendix B are fairly identical to our main results in Table 5.

Finally, Expedia brought back American fares after 3 months. To verify if the results are robust to this smaller time window, Table 28 in Appendix B shows this change for this 3-month period. As can be seen, the effects are similar.

4.1.3 Total Searches

In this section, we test to see if the dispute had an impact on the total number of searches conducted by a consumer: do consumers augment their searches causing an increase in total sites visited, do they drop a few websites causing a decrease, or does the total search intensity remain unchanged. To conduct this analysis, we include all months (per individual) irrespective of whether a search was conducted. We then evaluate 1) changes in the total intensity of search, and 2) whether the treated firms exhibit the same patterns documented thus far.

We find, across all outcome measures, individuals search less during the dispute period. To understand if this is driven by individuals searching less at airlines, or aggregators, or both, we split the outcome measures by searches at each group. Table 8 reports the results for Total Searches, Searches at Aggregators, and Searches at Airlines. We find that most of the decline in searches comes from a drop in aggregator usage. Airline usage is largely unchanged with the exception of pages visited which sees a drop. Taken together these results indicate that without comprehensive aggregators, aggregators stand to lose, and perhaps to some extent airlines as well because consumers might now find poorer matches. However, to conclusively state if these changes are economically meaningful we rely on the demand analysis conducted in Section 4.3.

We further find, similar to our main analysis, that search patterns on this expanded dataset indicate a decline in site visits at Orbitz and Expedia (Table 9). Moreover, as a percentage change, these numbers are fairly identical to our main analysis: 10.8% for Orbitz and 9% for Expedia.

Table 8: Total Searches

(1) All		sites		duration		pages	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.126	13.09	0.987	11.56	1.182	14.20
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**-0.063**	**-3.99**	**-0.477**	**-3.48**	**-0.716**	**-4.95**
(2) Aggregators		sites		duration		pages	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.096	13.88	0.763	12.03	0.777	13.77
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**-0.063**	**-5.52**	**-0.467**	**-4.77**	**-0.365**	**-4.38**
(3) Airlines		sites		duration		pages	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.030	6.24	0.224	5.07	0.405	7.85
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.001**	**0.08**	**-0.010**	**-0.13**	**-0.351**	**-3.30**
N obs	1,267,152						
N id	82,886						
Fixed effects	id, year						
Cluster	id						

Note: Table presents a diff analysis across (1) all domains, (2) all aggregators, and (3) all airlines on the dependant measures total sites, total duration spent and total pages. The data is expanded to include months of no search. $\boldsymbol{\delta_1}$ is the relevant treatment effect.

Table 9: Diff-in-diff analysis including no-search months

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.008	13.06	0.007	12.76	0.006	11.58
Jan-May X Dispute	β_1	-0.004	-4.24	-0.003	-3.67	-0.003	-3.48
Jan-May X Focal	β_0^F	-0.002	-0.97	0.009	4.90	0.026	9.89
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.005**	**1.93**	**-0.009**	**-2.50**	**-0.014**	**-3.30**
N obs	21,541,584						
N id	82,886						
Fixed effects	Id, Year, Year X Focal						
Cluster	Id						

4.2 Heterogeneity

The literature on manufacturer-retailer interactions has two main theoretical predictions that relate to competition and loyalty. On competition, the literature (e.g., O'Brien and Shaffer 1997, Kadiyali et al 2000) suggests increased manufacturer competition makes for higher retailer market power. On loyalty, the literature suggests loyalty can relieve competition thus giving the manufacturer more power (see Ailawadi et al (2010) for a review of the theoretical work around this). Our setting allows us to empirically test these two theoretical predictions.

We operationalize manufacturer competition using the localized nature of airline competition that provides variation across airports[5]. We expect that in airports that face more competition (and have a strong American presence) the aggregators Expedia and Orbitz will not be significantly impacted during the dispute, i.e. the retailer has more power.

We operationalize loyalty to aggregators/airlines based on consumers' usage of aggregators/airlines. We expect the biggest change to occur among consumers who use multiple aggregators, i.e., users who are least loyal to Expedia/Orbitz.

In addition, we also expect that airports with no American presence will see little impact of the dispute. Similarly, airports where American is the most important airline will also see little impact of the dispute. Such users might be fairly well informed of American's offerings and primarily use aggregators to learn about competing airlines' offerings, which Orbitz and Expedia still offer. We test all three dimensions of heterogeneity (American presence, competition, loyalty) below.

4.2.1 Airports with No American Presence, High American Presence vs. the rest

We use the Airline Origin and Destination Survey (DB1B) database to infer the importance of each airline to an airport. We create an importance score, imp_{mj}, for each airline j -airport m combination as follows:

$$\text{imp}_{mj} = \frac{d_{mj}}{\sum_j d_{mj}}$$

where d_{mj} is the total number of passengers who flew from origin airport m in airline j across the years 2010-2012 and $\sum_j d_{mj}$ sums across all passengers for that airport across all top airlines.

The comScore data provides us with the zipcode of each individual user in the panel.

[5]We thank the Editor for this insight

From this, we infer the closest airport to each user, using the Euclidean distance between every airport and the center of the user's zipcode as our distance measure. We then merge the importance measure to the comScore data to determine if a consumer lives near an airport where American is absent or prominent.

We subset airports based on relative presence of American airlines: (1) those where American has no presence, i.e., $imp_{m,AA} = 0$. We consider the nearest as well as the second nearest airport to a consumer's zipcode if that second airport is within 50 miles, to allow for substitution between nearby airports. We also add the constraint that the airport have atleast one major airline operating, to avoid considering small regional airports where consumers might travel farther (for example, AHN is a regional airport with no major airlines, but a consumer can easily drive to ATL which is a 1.5hr/78 mile drive away) (2) those where American has a high presence, i.e., it is one of the top two airlines as measured by passengers served at that airport, and (3) those where American is neither absent nor most important[6]. We expect the impact of the dispute to be strongest for the last subset (3), where American is neither absent nor most important, because this is where the role of aggregators is most relevant.

Table 10 presents the results for each subset, as well as the results for the entire dataset. As expected, we do not see any effect on the treated firms at airports where American has no presence. Similarly, consumers living near airports with high American presence do not change their behavior. This is because they likely know about American and use aggregators to search for other airlines (such as United) for whom the aggregators are still useful. The last subset (3) is where we find the strongest effect of the dispute, supporting our hypothesis. Consumers who live close to an airport where another airline is prominent (e.g., United) drop their usage of Orbitz and Expedia. Such consumers might not be well informed of American's fares, and therefore might use aggregators to conduct a comprehensive search of their options. However, now that Orbitz and Expedia are not as informative, they are less useful. In fact, comparing the estimates of this subset to that using all the data, the results are stronger both in significance as well as magnitude.

We also repeat this exercise using a simple diff analysis, without using competitors to see if the direction of the results hold. Table 29 in Appendix B presents the results of this simple diff specification, confirming the direction of the effect.

[6]Airports with no American presence are typically small with an average yearly passenger count of 81 per airport. Airports include Adak Regional , Mid Delta Regional and Frank Wiley Field. Those that have high American presence include all of American's hubs (LAX, ORD, DFW, LGA, JFK and MIA) as well as many smaller regional airports like Waco Regional and Tyler Pounds Regional where American is the prominent player. Airports that are neither include big airports like Atlanta where Delta is the most important player and San Diego where Southwest is the most important player along with many smaller airports.

4.2.2 Competitive airports

Per the theoretical literature, we expect that in airports that face more competition (and have a strong American presence) the aggregators Expedia and Orbitz will not be significantly impacted during the dispute, i.e. the retailer has more power. We define each airport's competitiveness by their hhi measured as $hhi_m = \sum \left(\frac{d_{mj}}{\sum_j d_{mj}}\right)^2$ where d_{mj} is the passenger demand for airport m and airline j. We define a high competition airport for American as one where 1) $hhi < 0.18$ which is the 75th percentile across all airports (the mean hhi is 0.14). and 2) American has a significant presence, i.e., it forms atleast 10% of the passenger demand at that airport. We add this restriction because we are not interested in high competition airports where the competition is between two un-treated airlines. We also consider American's hubs: American has 6 hubs all of which are fairly competitive. Finally, we identify cities that have multiple hubs at different airports atleast one of which is an American hub. As an example, Chicago has ORD (United, American), MDW (Southwest) and MKE (Southwest and Airtran). Therefore, we include consumers who live near all three airports and not just those who live near ORD

We combine all three measures of competition: airports that are hubs for multiple airlines, cities that have multiple hubs at different airports, and airports that have high competition. Airports that satisfy all three criteria are LAX, LGA and ORD. On the other extreme, we classify as low competition, airports that are not hubs for multiple airlines and are not in cities that have multiple hubs, and have low competition as defined by $hhi \geq 0.18$. In addition, we exclude airports with no American presence or high American presence to ensure we analyze areas where the aggregator is needed (per the analysis in Section 4.2.1 the aggregator's function is minimal in these two extremes of American's presence). 81 airports satisfy this criteria and are included in the "low competition" analysis. Tables 11 and 30 show the diff-in-diff analysis as well as simple diff analysis. These tables show that the retailers (Orbitz and Expedia) are not impacted in areas where there is high competition. Finally, we note that our data does not have enough power to do a D-D-D analysis between areas with low competition and the rest.

4.2.3 Loyalty: Multiple vs single use of aggregators/airlines

Section 3.1 documents the difference in consumers' usage behavior of aggregators and airlines, with some consumers visiting only 1 aggregator and others visiting multiple aggregators. Given this difference in usage behavior, we conduct the analysis separately on these different groups. We expect those who use multiple aggregators will see the biggest change in behavior. Table 12 validates our hypothesis. Column (3) suggests those who use Expedia combined with other aggregators during search, are the ones who stop using Expedia during the dispute. Column (1) suggests those who use only Expedia to inform their search do not change their behavior during the dispute period. A similar pattern holds for Orbitz as well, seen in Table 13. This analysis shows that competition in the aggregator space matters: the decline is strongest among users who view aggregators as close substitutes.

We repeat the same exercise, but now as defined by consumers' usage of American, reported in Table 14. Column (1) of Table 14 suggests those loyal to American increase their browsing on American during the dispute period. This pattern does not replicate for those users not loyal towards American. Examining the group of loyal users further, we split them into those who use aggregators vs. those who do not. We find the increase in visits to American is driven by those who use aggregators (Table 15). We confirm this is driven by users who visit Orbitz and Expedia, and not just any aggregator. We therefore believe this pattern occurs because information is unavailable on two of the aggregators, such users come to American more often. As a placebo check, we repeat the same exercise as defined by consumers' usage of Delta and do not find such a pattern (Table 16).

Note that while the above grouping is indicative of users' loyalty, it is also contaminated by the treatment (for example, American might have users that are more loyal during the dispute because of the dispute). Therefore, for all of these analyses, we expand the dataset to include months of no-search as well to allow for changes in the extensive margin thus mitigating such a concern.

Table 10: Site visits for consumers living near airports with varying degrees of American presence: diff-in-diff

(1) No American Airlines serving nearby airports

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.082	1.35	0.079	1.36	0.070	1.32
Jan-May X Dispute	β_1	-0.038	-0.53	-0.038	-0.53	-0.023	-0.34
Jan-May X Domain	β_0^F	-0.042	-1.06	0.006	0.06	0.160	0.74
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**0.046**	**0.7**	**0.037**	**0.33**	**-0.220**	**-0.96**
N obs	20,451						
N	469						

(2) American is most important airline in nearest airport

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.006	0.77	0.006	0.9	0.004	0.62
Jan-May X Dispute	β_1	0.022	1.89	0.019	1.69	0.022	1.97
Jan-May X Domain	β_0^F	0.011	0.59	-0.001	-0.04	0.033	1.39
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**-0.017**	**-0.56**	**0.034**	**0.77**	**-0.021**	**-0.58**
N obs	1,035,283						
N	20,248						

(3) Airport is neither American-absent or American-important

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.027	8.21	0.024	7.56	0.021	7.16
Jan-May X Dispute	β_1	-0.018	-3.3	-0.012	-2.27	-0.012	-2.38
Jan-May X Domain	β_0^F	-0.010	-1.27	0.041	4.7	0.086	6.16
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**0.034**	**2.59**	**-0.065**	**-3.78**	**-0.064**	**-2.68**
N obs	3,238,738						
N	60,788						

All data

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.022	7.23	0.020	6.77	0.017	6.14
Jan-May X Dispute	β_1	-0.008	-1.72	-0.005	-0.99	-0.004	-0.84
Jan-May X Domain	β_0^F	-0.006	-0.77	0.031	3.59	0.074	6.1
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**0.023**	**1.85**	**-0.041**	**-2.42**	**-0.054**	**-2.7**
N obs	4,298,671						
N	81,418						

Note: This table presents a diff-in-diff analysis for visits to the treated domains for three subsets of the data, 1) airports with No American presence, 2) Airports where American is the most important airline and 3) the rest. The hypothesis is that we will see the strongest effect of the dispute in susbet (3), because this is where the role of aggregators is most relevant. For reference, analysis using All data is also presented. A few individuals do not have an associated zipcode and therefore drop out of this analysis. $\boldsymbol{\beta_1^F}$ is the relevant treatment effect.

Table 11: Site visits for consumers living near airports with varying degrees of competition: diff-in-diff

(1) High competition airports

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.025	1.47	0.028	1.8	0.028	1.7
Jan-May X Dispute	β_1	-0.001	-0.04	0.002	0.07	0.001	0.02
Jan-May X Domain	β_0^F	0.079	1.66	0.030	0.44	0.024	0.39
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**-0.033**	**-0.5**	**-0.084**	**-0.99**	**-0.061**	**-0.68**
N obs	216,270						
N	4,110						

(2) Low competition airports

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.022	4.33	0.019	3.89	0.017	3.58
Jan-May X Dispute	β_1	-0.018	-2.17	-0.011	-1.39	-0.011	-1.36
Jan-May X Domain	β_0^F	0.007	0.62	0.054	3.99	0.092	4.95
Jan-May X Dispute X Domain	$\boldsymbol{\beta_1^F}$	**0.030**	**1.34**	**-0.083**	**-2.24**	**-0.093**	**-2.08**
N obs	939,420						
N	19,312						

Table 12: Diff-in-diff analysis by varying degrees of Expedia's market power

		(1)		**(2)**		**(3)**	
		Only Expedia		Expedia and 1-2 others		Expedia and more than 2 others	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.001	2.50	0.003	4.89	0.013	9.32
Jan-May X Dispute	β_1	0.001	1.43	0.001	0.42	-0.006	-2.65
Jan-May X Expedia	β_0^F	0.033	3.02	0.025	3.60	0.054	9.51
Jan-May X Dispute X Exp.	$\boldsymbol{\beta_1^F}$	**-0.002**	**-0.14**	**-0.014**	**-0.97**	**-0.032**	**-3.34**
N obs		2,352,732		4,017,168		6,985,368	
N		10,746		16,522		22,301	

Note: Table presents 3 separate regressions for each of the three groups of users: (1) those who browse only Expedia and no other aggregator, (2) those who browse Expedia and 1-2 other aggregators, and (3) those who browse Expedia and more than 2 other aggregators. The last group are the least loyal to Expedia, and we expect these users to drop their site visits to Expedia.

Table 13: Diff-in-diff analysis by varying degrees of Orbitz's market power

		(1)		**(2)**		**(3)**	
		Only Orbitz		Orbitz and 1-2 others		Orbitz and more than 2 others	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.001	1.18	0.003	2.58	0.016	9.83
Jan-May X Dispute	β_1	-0.001	-0.51	-0.003	-1.19	-0.009	-3.05
Jan-May X Orbitz	β_0^F	0.017	2.27	0.009	1.03	0.033	5.98
Jan-May X Dispute X Orbitz	$\boldsymbol{\beta_1^F}$	**0.005**	**0.36**	**0.007**	**0.28**	**-0.032**	**-3.80**
N obs		604,452		2,078,148		5,938,848	
N		2,669		8,403		18,563	

Note: Table presents 3 separate regressions for each of the three groups of users: (1) those who browse only Orbitz and no other aggregator, (2) those who browse Orbitz and 1-2 other aggregators, and (3) those who browse Orbitz and more than 2 other aggregators. The last group are the least loyal to Orbitz, and we expect these users to drop their site visits to Orbitz.

Table 14: Diff-in-diff analysis by varying degrees of AA's market power

		Only AA		AA and 1-2 others		AA and more than 2 others	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.006	3.29	0.012	5.95	0.016	4.27
Jan-May X Dispute	β_1	-0.004	-1.45	-0.002	-0.54	-0.007	-1.07
Jan-May X AA	β_0^F	-0.002	-0.11	0.024	2.18	0.009	0.97
Jan-May X Dispute X AA	$\boldsymbol{\beta_1^F}$	**0.068**	**2.86**	**-0.015**	**-0.83**	**0.005**	**0.32**
N obs		804,168		1,870,068		2,270,520	
N		3,603		6,478		5,121	

Note: Table presents 3 separate regressions for each of the three groups of users: (1) those who browse only AA and no other airlines, (2) those who browse AA and 1-2 other airlines, and (3) those who browse AA and more than 2 other airlines.

Table 15: Diff-in-diff analysis for those who browse only AA: by varying degrees of aggregator usage

		Only AA			
		No aggregator		**Use aggregators**	
		coeff	t-stat	coeff	t-stat
Jan-May	β_0	N/A	N/A	0.009	3.30
Jan-May X Dispute	β_1	N/A	N/A	-0.005	-1.40
Jan-May X AA	β_0^F	0.038	1.74	-0.018	-0.85
Jan-May X Dispute X AA	$\boldsymbol{\beta_1^F}$	**-0.001**	**-0.03**	**0.098**	**3.12**
	N obs	243,780		560,388	
	N	1,168		2,435	

Note: Table presents 2 separate regressions for the subset of users who browse only American and no other airline. This group is further susbet into those who never use aggregators and those who use atleast one aggregator.

Table 16: Placebo check: Diff-in-diff analysis by varying degrees of Delta's market power

		Only Delta		**Delta and 1-2 others**		**Delta and more than 2 others**	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.004	2.53	0.014	7.22	0.019	5.54
Jan-May X Dispute	β_1	0.000	0.16	-0.008	-2.83	-0.009	-1.59
Jan-May X AA	β_0^F	-0.014	-0.76	0.010	1.15	-0.011	-0.99
Jan-May X Dispute X AA	$\boldsymbol{\beta_1^F}$	0.021	0.61	-0.023	-1.38	0.030	2.01
N obs		959,820		2,121,192		2,431,272	
N		4,282		7,287		5,418	

Note: Table presents 3 separate regressions for each of the three groups of users: (1) those who browse only Delta and no other airlines, (2) those who browse Delta and 1-2 other airlines, and (3) those who browse Delta and more than 2 other airlines.

4.3 Demand: Purchases on aggregators and airlines

We now explore whether the dispute period had an impact on purchases. We first use the comScore data, which track transactions at the domain level, to measure changes in Orbitz's and American's purchases. Note that because comScore tracks only online transactions, we might miss any airline sales that occurred through other channels such as offline travel agents or over the phone. To account for all sales, we therefore use the DB1B database to measure the total impact of the dispute on American's sales.

The comScore data also does not have an accurate measure of prices. Prices are unobserved if there was no transaction. Although prices can be constructed from publicly available data, we do not know the (potential) destination of the consumer. Therefore, our analysis in section 4.3.2 which uses the DB1B database and which has prices at the quarterly level for every origin-destination pair and carrier will help us further account for prices in the demand estimation.

4.3.1 Airline and aggregator demand: comScore data

We first expand the data to include the outside option. We do so to allow for the fact that users might use other channels (e.g. offline travel agents) to make their airline bookings or choose not to participate in the airline market. We include both 1) all months of search as potential months when a consumer could have purchased a ticket and 2) only the last month of search as a potential month of purchase. The latter option is closer to reality because those who buy always purchase on the last month of browsing, so one can assume safely that for all no purchases, they would have purchased in the last month of search.

For each individual-month-option, we specify the utility to be:

$$u_{ijt} = \alpha_{0j} D_t + \alpha_{1j} D_t \times Dispute_Y + \gamma Ad_{jt} + \alpha_{jtY} + \varepsilon_{ijt} \tag{4}$$

where D_t is an indicator for the dispute months (Jan-May) in any year, $Dispute_Y$ is the treatment year 2011. Ad_{jt} is the total advertising spend in that month. α_{1j} is the treatment effect. α_{jtY} are year fixed effects. We consider four possible options: 1) the outside option or the no purchase option, 2) purchase on the treated aggregators Orbitz and Expedia, 3) purchase on any of the other aggregators, and 4) purchase on any airline (excluding American[7]). We construct the advertising variable, Ad_{jt}, as the sum of Ad spend of all firms within each option.

Assuming the unobserved (to the researcher) shocks follow a Type-1 extreme-value distribution, the probability that individual i books at website j in month t is given by

$$\Pr_{ijt}(\alpha) = \frac{e^{u_{ijt}(\alpha)}}{\sum\limits_{k \in C} e^{u_{ikt}(\alpha)}}$$

The overall log-likelihood across all individuals can then be written as

$$LL(\alpha) = \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{C} log \Pr_{ijt}^{\mathrm{I}_{ijt}}(\alpha)$$

where I_{ijt} is 1 if individual i booked option j in month t, and C is the choice set available to the individual, which includes all airlines and all aggregators.

[7] to avoid any bias that inclusion of the treated firm might cause. We thank a reviewer for this suggestion.

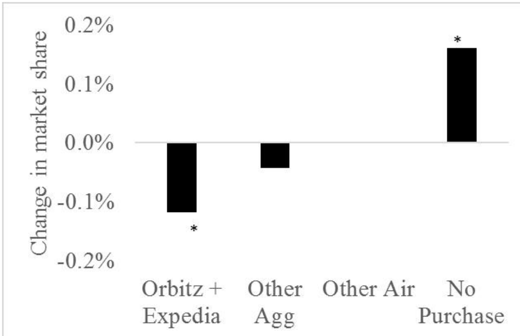
Table 17 and Figure 5 show the results of the demand estimation. The results indicate during the dispute Orbitz and Expedia see a significant decline in purchases. While there is a decline in other aggregators and other airlines, this decline is neither statistically nor economically significant. Most of the decline goes to the outside option[8] (which could be consumers using offline travel agents, using other means of transportation, purchasing through an aggregator/airline not included in the analysis, or not participating in the market at all). Using the DB1B data (below) we find sales of American remains unchanged during the dispute, indicating that it is likely consumers used other means of booking their tickets: a *Washington Post* (2011) article points to a shift to offline travel agents in 2011.

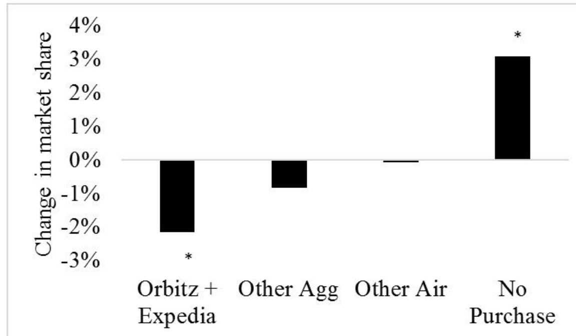
[8]We verify the increase in the "no purchase" option with a simple descriptive regression indicating the result is not from a functional form specification.

Table 17: Demand Estimates using comScore Data

		All months (1)		Last month (2)	
Base: No Purchase					
Orbitz + Expedia		coeff	t-stat	coeff	t-stat
Jan-May	α_{0j}	0.316	7.53	1.050	23.51
Jan-May X Dispute	$\boldsymbol{\alpha_{1j}}$	**-0.334**	**-4.30**	**-0.372**	**-4.69**
Year = 2011	$\alpha_{j,2011}$	0.011	0.20	0.048	0.85
Year = 2010	$\alpha_{j,2010}$	0.101	2.38	0.135	3.11
Constant	α_j	-6.070	-153.41	-3.601	-86.65
Other Aggregators					
Jan-May	α_{0j}	0.137	2.89	0.874	16.90
Jan-May X Dispute	$\boldsymbol{\alpha_{1j}}$	**-0.034**	**-0.42**	**-0.102**	**-1.24**
Year = 2011	$\alpha_{j,2011}$	0.221	3.49	0.243	3.77
Year = 2010	$\alpha_{j,2010}$	0.352	6.67	0.361	6.86
Constant	α_j	-6.343	-98.20	-3.852	-55.45
Other Airlines					
Jan-May	α_{0j}	0.102	4.60	0.836	30.68
Jan-May X Dispute	$\boldsymbol{\alpha_{1j}}$	**-0.014**	**-0.36**	**-0.068**	**-1.62**
Year = 2011	$\alpha_{j,2011}$	-0.302	-10.75	-0.266	-8.97
Year = 2010	$\alpha_{j,2010}$	-0.315	-14.24	-0.287	-12.08
Constant	α_j	-4.420	-193.73	-1.953	-73.57
Ad	γ	2.47E-05	0.37	4.00E-04	0.44
N obs		1,265,717		100,615	

Note: (1) presents results of a multinomial logit where the outside option of no purchase is constructed using all months all months of search as potential months when a consumer could have purchased a ticket, (2) presents the results assuming the last month of a search is when a purchase would have occurred. Each observation is a purchase at Orbitz or Expedia, at any other aggregators, at any airlines (excluding American), or a no purchase.





(1) (2)

(1): No purchase constructed using all months of search as potential months when a consumer could have purchased a ticket
(2): No purchase constructed using last month of search.

Figure 5: Change in market-share during dispute: Orbitz+Expedia see decline in purchases

To the extent that the tickets booked on Orbitz and Expedia might have been American tickets, this is also potential evidence that American Airlines might also have been impacted negatively. Therefore, to verify whether total demand for American Airlines changes, we use the DB1B database, which tracks passengers (demand) by origin-carrier-quarter.

4.3.2 Airline demand: DB1B data

The DB1B data track the number of passengers who fly per quarter through each carrier for every origin-destination pair combination. We use this data to measure changes in American's total demand during the dispute period. This exercise is similar in spirit to Bilotkach et al (2017), who find that demand for American did not change during the dispute period. Similar to their approach, we drop (1) observations with fares that are less than $0.02 per mile that are flagged as questionable, (2) markets, i.e., Origin-Destination pairs, with less than 100 passengers in a quarter, (3) itineraries that are not round-trips, and (4) itineraries that have more than 1-stop, i.e., we keep only non-stop and 1-stop itineraries. Itineraries that have the same origin-destination but go through varying stops/layovers are treated equally for purposes of the estimation. For example, we do not distinguish between LAS:CLT:ABE and LAS:PHL:ABE, itineraries with 1 layover originating at Las Vegas (LAS) and ending at Lehigh Valley (ABE). The difference between our approach and Bilotkach et al.'s (2017) is that we include data from and control for the non-dispute quarters as well: this approach allows us to account for any yearly changes in demand that might not have anything to do with the dispute period. We also include the future year (2012) as an additional control and include the top nine airlines (to be consistent with the comScore demand estimation). Finally, we also consider the outside option. We use each zipcode's population to create the market share of the outside option.

We model demand for airline j in a given market (O-D pair) m in quarter t, relative to the outside option as:

$$\begin{aligned} ln\left(s_{jmt}\right) - ln\left(s_{0mt}\right) = & \alpha_0 Disp_t + \alpha_0 Disp_t \times T_Y \\ & + \alpha_0^F Disp_t \times Focal_j + \alpha_1^F Disp_t \times T_Y \times Focal_j \\ & + \gamma X_{jt} + \alpha_{tY} + \alpha_j + \alpha_{j,tY} + \alpha_m + \varepsilon_{ijt} \end{aligned} \tag{5}$$

Here, s_{mjkt} is the share of passengers that flew airline j in origin-destination (O-D) pair m with number of stops k in quarter t, relative to all passengers flying that given O-D pair with the same number of stops and in the quarter. $Disp_t$ is an indicator for the dispute months (Jan-May) in any year, T_Y is the treatment year 2011, $Focal_j$ is the treated firm American. X_{jt} is the vector of other independent variables such as price, Ads, distance, number of stops. α_1^F is the treatment effect. α_{tY}, α_j and $\alpha_{j,tY}$ are year, carrier and year-carrier fixed effects respectively. α_m is the O-D fixed effect. We instrument for price using jet fuel costs (at the carrier-year-quarter level), number of stops in the itinerary, and the distance between Origin and Destination.

The results of this estimation are reported in Table 18. We find that α_1^F is not statistically significant from zero, suggesting demand for American Airlines did not change during the dispute period.

Table 18: Demand Estimates using DB1B data

		coeff	t-stat
Dispute	α_0	-0.281	-3.09
Dispute X Treatment	α_1	0.000	0.00
Dispute X AA	α_0^F	0.050	0.50
Dispute X Treatment X AA	$\boldsymbol{\alpha_1^F}$	**-0.092**	**-1.58**
price	γ_P	-0.033	-3.55
Ads	γ_{Ad}	2.2E-07	1.28
N obs	561,689		
N O-D	12,337		
Fixed effects	O-D		
	Year		
	Carrier		
	Carrier-Year		
Cluster	O-D		
	Carrier		
price IV	fuel cost		
	stops		
	distance		

4.4 Economic significance

The average site visits on Orbitz, across all users who visit travel-related websites, is 0.38. Compared to this value, a drop in monthly site visits of 0.036 (Table 5) amounts to an 10% decline. To put this decline in perspective, as of year-end 2010, Orbitz's yearly revenue from advertising and media revenue was \$49.4m, accounting for 6.5% of its total revenue (Orbitz 10K, 2010). For Orbitz, advertising and media revenue largely consists of revenue from display ads, which is directly proportional to the number of site visits. With an 10% decline in site visits, the drop in Orbitz's revenue is \$4.68m. Similarly, Expedia would face a revenue loss of \$7.28m.

Orbitz's standalone air revenue was \$274.6 year-end 2010, and \$265m year-end 2011, implying a 3% decline in air revenue from 2010 to 2011. This amount is close to our estimated 2.16% decline in market-share reported in section 4.3.1, Figure 5. These numbers show that Orbitz lost a significant source of its revenue stream during the dispute period.

4.5 Discussion

The event study design assumes the only change that occurred during the treatment period is the American-Orbitz dispute. To the extent other events might have occurred in the travel industry we are measuring the net effect of these events. Two events that might be of concern are the United-Continental merger that was announced in May 2010 and transpired in November 2011, and the American's bankruptcy filing in November 2011. However, the following findings give us greater confidence that we are indeed measuring the impact of the dispute. First, while we might expect American Airlines to be impacted by these events, Orbitz and Expedia should not be disproportionately (compared to other aggregators) impacted by these events. The fact that these two aggregators are the ones that see a drop in visits give us greater confidence that we are indeed measuring the impact of the dispute. This drop in visits for these two aggregators hold under a host of robustness checks. Second, in our loyalty analysis we find that the group of users who are most loyal to American airlines and use aggregators to augment their search, are the ones who increase their site visitation on American. Users who are not loyal to American (i.e., visit multiple other airlines) do not exhibit this increase, nor do users who are completely loyal to American but do not augment their search with aggregators. Moreover, Delta users do not exhibit such a pattern. If American is benefited because of the United Continental merger, then we should not see a disproportionate increase in American's visits by American loyalists who use aggregators, and no increase by American loyalists who do not visit any other site. It is also unclear why American, and not Delta, should be likely to benefit from this merger. The dispute explains these patterns better.

Finally, it is possible that in response to the dispute, the impacted domains as well as their competitors, could have altered their marketing variables. We therefore verify airlines' prices and all travel websites' advertising responses in the following section. If firms made changes to other marketing variables for which we do not have data, such changes would not be captured.

5 Firm Response

5.1 Prices

We first check for airlines' price responses, where prices are observed using the DB1B database. This exercise is similar in spirit to Bilotkach et al (2017), who find that American's fares dropped during the dispute period. We subset the DB1B using the same criteria described in Section 4.3.2. We calculate the average fare at the airline-year-quarter-origin-destination-number of stops level. The difference between our approach and Bilotkach et al.'s (2014) is that we include data from and control for the non-dispute quarters as well: this approach allows us to control for any yearly changes in prices that might not have anything to do with the dispute period; for example, if American dropped its prices in 2011, merely including 2011 Q1 data might mislead us to infer the drop was due to the dispute. We also include the future year (2012) as an additional control and include the top nine airlines (to be consistent with the demand estimation). Finally, we also control for jet fuel costs which vary by airline and month, available from the Bureau of Transportation Statistics[9].

The basic price regression we estimate is:

$$\begin{aligned} ln\left(p_{mjkt}\right) &= \delta_0 D_t + \delta_1 D_t \times Disp_Y \\ &+ \delta_0^F D_t \times Focal_j + \delta_1^F D_t \times Disp_Y \times Focal_j \\ &+ \alpha_{tY} + \alpha_{tY}^F Focal_j + \alpha_j + \alpha_m \\ &+ \delta_3 cost_{jt} + \varepsilon_{mjkt} \end{aligned} \tag{6}$$

where m is an Origin-Destination pair, j is the airline, k is the number of stops, and t is the quarter. Here, p_{mjkt} is the passenger-weighted average airfare charged by airline j in market m with number of stops k in quarter t . We add additional controls, such as the number of stops and distance between the origin and destination.

Table 19 reports results of this regression using various controls. δ_1^F gives us the change in American's prices relative to competitors and the baseline years. Specification (1) reports the estimates from the basic regression in equation 6, which controls for origin-destination, year, and carrier fixed effects. Specification (2) adds controls for carrier-year fixed effects as well, (3) adds the distance between the origin-destination pair as an additional control, (4) adds market share, and (5) adds a control for the number of stops. As can be seen, American fares in 2011 seem to decrease relative to 2010 and 2012. However, this decrease is not statistically significant. This pattern is true across all specifications (1)-(5). Moreover, this result is robust to using the unweighted average fare as well.

While these results are directionally consistent with Bilotkach et al.'s (2017) findings, unlike their finding we find little evidence of a statistically significant drop. One possible reason for this difference is our inclusion of jet fuel costs as an explanatory variable. Figure 6 plots the difference in jet fuel prices between American and all major carriers. We see that American faced lower fuel costs during the dispute period. Therefore, not including this cost control attributes all the change in prices to the dispute. American's 10k report, which states that due to the company's fuel hedging program they saw a decrease in fuel expenses

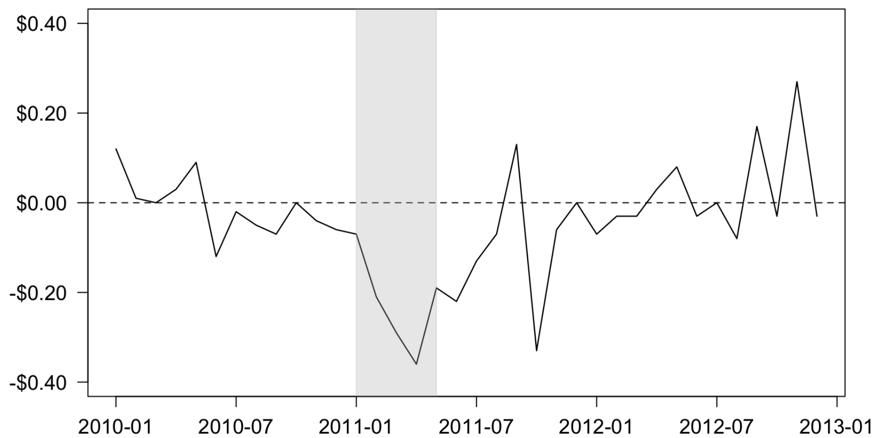
[9]https://www.transtats.bts.gov/fuel.asp

in 2011 (American 10K, 2011), is consistent with figure 6.

Table 19: Prices during the dispute and control periods: Estimates using DB1B data

	1		2		3		4		5	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
δ_0	-0.0228	-18.66	-0.0222	-18.15	-0.0222	-18.23	-0.0216	-17.82	-0.0222	-18.24
δ_1	-0.0024	-1.13	0.0017	0.75	0.0013	0.60	0.0012	0.55	0.0015	0.67
δ_0^F	-0.0033	-1.20	-0.0031	-1.16	-0.0025	-0.94	-0.0039	-1.45	-0.0036	-1.33
$\boldsymbol{\delta_1^F}$	**-0.0032**	**-0.69**	**-0.0019**	**-0.43**	**-0.0022**	**-0.48**	**-0.0022**	**-0.49**	**-0.0034**	**-0.75**
log(cost)	0.0440	4.53	0.0888	7.96	0.0898	8.13	0.0933	8.47	0.0936	8.52
distance					0.0002	48.39	0.0002	53.35	0.0001	33.82
mkt. share							0.0185	36.13	0.0143	28.91
num. stops									0.0761	38.15
N obs	562,252									
N O-D pairs	12,531									
Fixed-effects	O-D Year Carrier		O-D Year Carrier Carrier-Year		O-D Year Carrier Carrier-Year		O-D Year Carrier Carrier-Year		O-D Year Carrier Carrier-Year	
Addn. Controls					distance		distance mkt. share		distance mkt. share num. stops	

Note: Table presents diff-in-diff regression results for log(weighted market fare) with a number of different controls. DB1B quarterly data at the market (O-D), carrier level used.



Note: The grey shaded area represents the dispute months, January-May 2011.
Source: Bureau of Transportation Statistics.

Figure 6: Difference between American's and All Major Carriers' Cost per gallon of airline fuel (dollars)

5.2 Advertising

We use the Nielsen Monitor-Plus Media data, which consists of National TV, Spot TV, Internet, Magazines, Newspapers, Outdoors and Radio ad spend along with the airing date and the advertised brand. We focus on ad spend as the relevant metric and verify if any of the impacted domains changed their ad spend in the dispute period using the regression specification

$$\begin{aligned} ln\left(Ad_{jt}\right) = & \gamma_0 D_t + \gamma_1 D_t \times Disp_Y \\ & + \gamma_0^F D_t \times Focal_j + \gamma_1^F D_t \times Disp_Y \times Focal_j \\ & + \alpha_{tY} + \alpha_{tY}^F Focal_j + \varepsilon_{ijt} \end{aligned} \tag{7}$$

where Ad_{jt} is the advertising spend of brand j in month t. $D_t = 1$ if t is between January and May, the months relevant to the dispute period, $Disp_Y = 1$ if the months correspond to the year the dispute occurred (2011). $Focal_j$ is an indicator that equals 1 if travel domain j is the impacted domain, i.e., American, Orbitz, or Expedia. We test is $\gamma_1^F = 0$ which would imply ad spend in the control and dispute periods are similar. Table 20 reports the relevant estimate, γ_1^F, for each of the advertising media types for which we have data.

Table 20: Change in log of Ad Spend, relative to competitors and control period

	aa.com		orbitz.com		expedia.com		N obs
	coeff	t-stat	coeff	t-stat	coeff	t-stat	
Internet	-1.690	-1.93	-1.496	-2.41	-2.651	-4.43	991
Magazines	-3.654	-2.78	-0.352	-0.34	-4.686	-4.34	769
Network TV	-3.915	-5.56	-0.885	-1.04	-0.723	-0.80	514
Spot TV	-1.773	-2.16	0.290	0.39	-0.851	-1.09	815
Newspapers	0.002	0.00	N/A	N/A	0.990	1.51	707
Outdoors	-1.543	-1.40	N/A	N/A	N/A	N/A	480
Radio	-1.143	-2.05	N/A	N/A	-1.479	-3.57	688
Cluster	Brand						
Observation	Brand x Sub-brand x year x month						

Overall, there appears to be a decline in ad spend by American. Both Orbitz and Expedia appear to have decreased their ad spend pertaining to display ads. There are insufficient observations in Newspaper, Outdoor and Radio to make meaningful conclusions. To better understand the decrease in display ad spend by the impacted domains, we look at each domain separately. Interestingly, we find that this relative decrease in ad spend is driven by other aggregators (Cheapflights, Priceline) and airlines (Alaska, JetBlue) increasing their ad spend during the dispute period. This could be a competitive response by players such as Priceline and Cheapflights to make the most of Orbitz's shortcomings during the dispute period. Both Orbitz and Travelocity increased their magazine spending, partly influencing the relative decline in American's and Expedia's magazine ad spend. All these changes in advertising spending, which could be strategic responses by firms and their competitors, further highlights the need to control for this marketing variable in our demand analysis (Equations 4 and 5). We now verify that our main search results are robust to controlling for ad spend. Table 21 reports the results of this estimation. We find that our results are robust to adding advertising controls.

Table 21: Searches on impacted domains, controlling for ad spend across all media

		aa.com		orbitz.com		expedia.com	
(1) sites							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.022	7.15	0.020	6.53	0.018	6.11
Jan-May X Dispute	β_1	-0.019	-3.84	-0.015	-3.05	-0.014	-2.92
Jan-May X Focal	β_0^F	-0.019	-2.48	0.027	3.13	0.061	5.10
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.032**	**2.62**	**-0.045**	**-2.75**	**-0.050**	**-2.52**
Ad spend	γ	1.38E-08	58.70	1.40E-08	59.79	1.29E-08	54.45
(2) duration							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.184	6.81	0.165	6.32	0.130	5.12
Jan-May X Dispute	β_1	-0.133	-2.99	-0.104	-2.37	-0.095	-2.21
Jan-May X Focal	β_0^F	-0.134	-1.57	0.199	2.30	0.787	7.29
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.160**	**1.05**	**-0.347**	**-2.77**	**-0.423**	**-2.48**
Ad spend	γ	1.11E-07	48.33	1.12E-07	48.82	1.05E-07	45.61
(3) pages							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.226	8.32	0.238	8.70	0.203	7.53
Jan-May X Dispute	β_1	-0.170	-3.40	-0.191	-3.72	-0.182	-3.58
Jan-May X Focal	β_0^F	0.313	2.69	0.112	1.55	0.716	7.58
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.361**	**-1.63**	**-0.001**	**-0.01**	**-0.091**	**-0.61**
Ad spend	γ	1.05E-07	46.50	1.05E-07	47.01	9.94E-08	44.12
N obs	4,389,417						
N id	82,886						
Fixed effects	id, year, year X focal						
Cluster	id						

6 Conclusion

In the context of the airline industry, we find that airlines have more market power than the aggregator. The aggregator stands to lose, in terms of consumers visiting its website and purchases, when it is not comprehensive. The consumer heterogeneity patterns in the data further support this conclusion. Consumers who live near airports where a non-American airline is prominent (e.g., United) drop their usage of Orbitz the most. It is for these consumers that American's flight and fare information is perhaps the most useful: they likely already know United's flights and fares and would want to know if there are other better offerings. Not finding information about a relevant competitor makes Orbitz a less useful site. For an aggregator where a sizable portion of the revenue comes from ad placements, this implies an economically significant drop in revenue.

Our finding accentuates the necessity of understanding market power on a case by case basis and is relevant to policy makers and regulatory authorities. In our setting, we find the biggest decline in usage of Orbitz and Expedia is among users who view aggregators as close substitutes, indicating our results might apply to settings where there are multiple aggregators and users can easily substitute between them. The findings might look very different in a category where there is only one dominant aggregator (e.g. Amazon in the online retail setting) or where there are numerous firms (e.g. the hotel industry). Even in such cases individual firms might have different degrees of market power. We hope future research will analyze more cases to understand the market power relationship in different contexts.

This paper examines a short-run effect, constrained by the dispute which lasted five months. Long-run effects might be very different and might lead to higher equilibrium prices. It might also lead to changes in airlines' marketing strategy if they choose to no longer be part of an aggregator, as airlines have to work harder to increase their probability of discovery.

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A Search Estimates: Alternative Control Groups

Table 22: Site visits to **aa.com** unchanged during the dispute period: Results robust to three different analyses

		sites		duration		pages	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
(1) before-after analysis							
Jan-May	δ_0	0.017	1.89	0.126	1.25	0.714	5.27
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.016**	**1.10**	**0.104**	**0.57**	**-0.618**	**-2.20**
N obs	258,201						
N id	82,886						
(2) diff-in-diff (unlikely competitors, Airtran & AlaskaAir, as controls)							
Jan-May	β_0	0.006	1.95	-0.004	-0.10	0.082	1.99
Jan-May X Dispute	β_1	0.009	1.47	0.161	1.86	0.195	1.22
Jan-May X AA	β_0^F	0.003	0.41	0.073	0.81	0.514	4.36
Jan-May X Dispute X AA	$\boldsymbol{\beta_1^F}$	**0.006**	**0.44**	**-0.046**	**-0.28**	**-0.657**	**-2.72**
N obs	774,603						
N id	82,886						
(3) diff-in-diff (LonelyPlanet as control)							
Dispute	β_0	0.010	3.56	0.046	1.59	0.104	2.64
Dispute X Treatment	β_1	-0.004	-0.79	0.025	0.53	-0.059	-0.88
Dispute X AA	β_0^F	0.002	0.27	0.051	0.61	0.513	4.49
Dispute X Treatment X AA	$\boldsymbol{\beta_1^F}$	**0.016**	**1.36**	**0.019**	**0.13**	**-0.517**	**-2.39**
N obs	525,300						
N id	83,991						
(3) diff-in-diff analysis (exclude treated websites from control)							
Jan-May	β_0	0.015	5.44	0.106	4.41	0.158	5.90
Jan-May X Dispute	β_1	-0.005	-1.25	-0.007	-0.17	-0.089	-1.73
Jan-May X AA	β_0^F	0.000	0.03	0.034	0.40	0.469	4.04
Jan-May X Dispute X AA	$\boldsymbol{\beta_1^F}$	**0.018**	**1.47**	**0.044**	**0.29**	**-0.432**	**-1.95**
N obs	3,873,015						
N id	82,886						
(4) diff-in-diff analysis (original)							
Jan-May	β_0	0.022	7.22	0.186	6.87	0.228	8.39
Jan-May X Dispute	β_1	-0.009	-1.87	-0.054	-1.22	-0.095	-1.92
Jan-May X AA	β_0^F	-0.006	-0.81	-0.034	-0.40	0.407	3.51
Jan-May X Dispute X AA	$\boldsymbol{\beta_1^F}$	**0.023**	**1.90**	**0.090**	**0.59**	**-0.428**	**-1.94**
N obs	4,389,417						
N id	82,886						
Fixed effects	machine_id						
Cluster	machine_id						

Note: (1) presents a before-after analysis for visits to the domain aa.com. (2) presents a diff-in-diff analysis comparing searches of those who browsed American airlines to those who browsed unlikely competitors Alaska and AirTran. (3) presents a diff-in-diff analysis using visits to LonelyPlanet as a control. (4) presents a diff-in-diff analysis using all competitors (airlines and aggregators) except the treated firms as controls. (5) presents a diff-in-diff analysis using all competitors as controls. Each table presents 3 separate regressions run for each of the 3 dependant variables - sites, duration and pages. $\boldsymbol{\delta_1}$ in (1) and $\boldsymbol{\beta_1^F}$ in (2),(3), (4) and (5) are the relevant treatment effects.

Table 23: Site visits to **orbitz.com** drop during the dispute period: Results robust to three different analyses

		sites		duration		pages	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
(1) before-after analysis							
Jan-May	δ_0	0.056	5.12	0.386	3.18	0.397	4.61
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**-0.035**	**-1.91**	**-0.321**	**-1.99**	**-0.103**	**-0.78**
N obs	258,201						
N id	82,886						
(2) diff-in-diff (unlikely competitors, Kayak & Cheapflights, as controls)							
Jan-May	β_0	0.021	5.64	0.112	3.02	0.106	4.21
Jan-May X Dispute	β_1	-0.008	-1.24	-0.041	-0.67	0.008	0.19
Jan-May X Or	β_0^F	0.025	2.76	0.228	2.58	0.210	2.88
Jan-May X Dispute X Or	$\boldsymbol{\beta_1^F}$	**-0.031**	**-1.82**	**-0.294**	**-2.27**	**-0.082**	**-0.73**
N obs	774,603						
N id	82,886						
(3) diff-in-diff (LonelyPlanet as control)							
Dispute		0.013	3.84	0.059	1.98	0.074	2.65
Dispute X Treatment		-0.001	-0.15	-0.007	-0.15	-0.019	-0.49
Dispute X AA		0.032	3.51	0.261	2.98	0.236	3.26
Dispute X Treatment X AA		**-0.038**	**-2.19**	**-0.314**	**-2.47**	**-0.057**	**-0.52**
N obs	525,300						
N id	83,991						
(3) diff-in-diff analysis (exclude treated websites from control)							
Jan-May	β_0	0.015	5.53	0.109	4.47	0.156	5.83
Jan-May X Dispute	β_1	-0.005	-1.16	-0.013	-0.30	-0.086	-1.68
Jan-May X Or	β_0^F	0.031	3.48	0.249	2.87	0.187	2.58
Jan-May X Dispute X Or	$\boldsymbol{\beta_1^F}$	**-0.038**	**-2.24**	**-0.296**	**-2.35**	**0.036**	**0.32**
N obs	3,873,015						
N id	82,886						
(4) diff-in-diff analysis (original)							
Jan-May	β_0	0.021	6.87	0.173	6.63	0.246	8.97
Jan-May X Dispute	β_1	-0.006	-1.21	-0.033	-0.75	-0.124	-2.43
Jan-May X Or	β_0^F	0.027	3.06	0.194	2.24	0.107	1.49
Jan-May X Dispute X Or	$\boldsymbol{\beta_1^F}$	**-0.036**	**-2.18**	**-0.272**	**-2.17**	**0.070**	**0.62**
N obs	4,389,417						
N id	82,886						
Fixed effects	machine_id						
Cluster	machine_id						

Note: (1) presents a before-after analysis for visits to the domain orbitz.com. (2) presents a diff-in-diff analysis comparing searches of those who browsed Orbitz to those who browsed unlikely competitors Kayak and Cheapflights. (3) presents a diff-in-diff analysis using visits to LonelyPlanet as a control. (4) presents a diff-in-diff analysis using all competitors (airlines and aggregators) except the treated firms as controls. (5) presents a diff-in-diff analysis using all competitors as controls. Each table presents 3 separate regressions run for each of the 3 dependant variables - sites, duration and pages. $\boldsymbol{\delta_1}$ in (1) and $\boldsymbol{\beta_1^F}$ in (2),(3), (4) and (5) are the relevant treatment effects.

Table 24: Site visits to **expedia.com** drop during the dispute period: Results robust to three different analyses

		sites		duration		pages	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
(1) before-after analysis							
Jan-May	δ_0	0.100	6.51	1.119	8.25	1.043	9.12
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**-0.037**	**-1.52**	**-0.453**	**-2.15**	**-0.177**	**-0.99**
N obs	258,201						
N id	82,886						
(2) diff-in-diff (unlikely competitors, Kayak & Cheapflights, as controls)							
Jan-May	β_0	0.023	5.45	0.155	3.73	0.116	3.78
Jan-May X Dispute	β_1	-0.005	-0.64	-0.039	-0.57	0.032	0.67
Jan-May X Ex	β_0^F	0.063	5.17	0.833	7.61	0.826	8.66
Jan-May X Dispute X Ex	$\boldsymbol{\beta_1^F}$	**-0.044**	**-2.15**	**-0.431**	**-2.48**	**-0.229**	**-1.53**
N obs	774,603						
N id	82,886						
(3) diff-in-diff (LonelyPlanet as control)							
Dispute		0.015	3.51	0.111	2.78	0.078	2.09
Dispute X Treatment		0.005	0.60	0.006	0.10	0.026	0.50
Dispute X AA		0.069	5.56	0.850	7.74	0.837	8.77
Dispute X Treatment X AA		**-0.048**	**-2.36**	**-0.438**	**-2.53**	**-0.193**	**-1.31**
N obs	525,300						
N id	83,991						
(3) diff-in-diff analysis (exclude treated websites from control)							
Jan-May	β_0	0.016	5.52	0.118	4.73	0.158	5.83
Jan-May X Dispute	β_1	-0.004	-0.97	-0.012	-0.29	-0.081	-1.58
Jan-May X Ex	β_0^F	0.069	5.70	0.854	7.88	0.803	8.48
Jan-May X Dispute X Ex	$\boldsymbol{\beta_1^F}$	**-0.050**	**-2.50**	**-0.433**	**-2.53**	**-0.110**	**-0.74**
N obs	3,873,015						
N id	82,886						
(4) diff-in-diff analysis (original)							
Jan-May	β_0	0.018	6.30	0.135	5.29	0.207	7.69
Jan-May X Dispute	β_1	-0.005	-1.08	-0.024	-0.57	-0.115	-2.28
Jan-May X Ex	β_0^F	0.067	5.60	0.836	7.74	0.762	8.07
Jan-May X Dispute X Ex	$\boldsymbol{\beta_1^F}$	**-0.049**	**-2.48**	**-0.417**	**-2.45**	**-0.085**	**-0.57**
N obs	4,389,417						
N id	82,886						
Fixed effects	machine_id						
Cluster	machine_id						

Note: (1) presents a before-after analysis for visits to the domain expedia.com. (2) presents a diff-in-diff analysis comparing searches of those who browsed Orbitz to those who browsed unlikely competitors Kayak and Cheapflights. (3) presents a diff-in-diff analysis using visits to LonelyPlanet as a control. (4) presents a diff-in-diff analysis using all competitors (airlines and aggregators) except the treated firms as controls. (5) presents a diff-in-diff analysis using all competitors as controls. Each table presents 3 separate regressions run for each of the 3 dependant variables - sites, duration and pages. $\boldsymbol{\delta_1}$ in (1) and $\boldsymbol{\beta_1^F}$ in (2),(3), (4) and (5) are the relevant treatment effects.

B Search Estimates: Robustness Checks

Table 25: Using only last 1 month as relevant to the (intended) purchase

		aa.com		orbitz.com		expedia.com	
(1) sites							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.094	9.93	0.091	9.70	0.090	9.66
Jan-May X Dispute	β_1	0.002	0.11	0.008	0.46	0.007	0.39
Jan-May X Focal	β_0^F	-0.011	-1.35	0.044	4.77	0.048	3.76
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.033**	**2.45**	**-0.075**	**-5.19**	**-0.054**	**-2.92**
(2) duration							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	1.873	19.90	1.841	19.76	1.808	19.67
Jan-May X Dispute	β_1	0.170	0.92	0.219	1.19	0.220	1.21
Jan-May X Focal	β_0^F	0.016	0.12	0.552	4.62	1.121	6.02
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.133**	**0.63**	**-0.696**	**-3.57**	**-0.719**	**-2.69**
(3) pages							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	1.463	17.94	1.476	17.94	1.444	17.61
Jan-May X Dispute	β_1	-0.167	-1.16	-0.180	-1.24	-0.171	-1.19
Jan-May X Focal	β_0^F	0.595	3.40	0.362	3.49	0.911	6.45
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.538**	**-2.34**	**-0.311**	**-1.87**	**-0.463**	**-2.45**
N obs	1,746,223						
N id	82,886						
Fixed effects	id, year, year X focal						
Cluster	id						

Note: Tables present diff-in-diff analyses using all competitors as controls for each of the three dependant variables (1) sites, (2) duration and (3) pages. Only the last month of search is used. Each table presents 3 separate regressions run for each of the impacted domains, aa.com, orbitz.com and expedia.com. Jan-May is an indicator for the five months January-May, Dispute is an indicator for the year of the dispute 2011, Focal is an indicator for the impacted domain $\boldsymbol{\beta_1^F}$ is the relevant treatment effect.

Table 26: Using only last 2 months as relevant to the (intended) purchase

		aa.com		orbitz.com		expedia.com	
(1) sites							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.049	12.30	0.046	11.93	0.046	11.93
Jan-May X Dispute	β_1	-0.011	-1.43	-0.005	-0.73	-0.006	-0.81
Jan-May X Focal	β_0^F	-0.018	-2.15	0.026	3.01	0.037	3.45
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.031**	**2.50**	**-0.058**	**-4.07**	**-0.050**	**-2.81**
(2) duration							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.685	17.35	0.659	17.01	0.631	16.77
Jan-May X Dispute	β_1	-0.133	-1.92	-0.094	-1.39	-0.095	-1.42
Jan-May X Focal	β_0^F	-0.060	-0.59	0.373	4.18	0.859	6.39
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.107**	**0.67**	**-0.556**	**-3.89**	**-0.546**	**-2.66**
(3) pages							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.594	17.14	0.602	17.31	0.568	16.68
Jan-May X Dispute	β_1	-0.208	-3.64	-0.224	-3.95	-0.214	-3.81
Jan-May X Focal	β_0^F	0.369	2.58	0.217	2.63	0.803	7.13
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.433**	**-2.27**	**-0.159**	**-1.27**	**-0.332**	**-2.11**
N obs	2,747,574						
N id	82,886						
Fixed effects	id, year, year X focal						
Cluster	id						

Note: Tables present diff-in-diff analyses using all competitors as controls for each of the three dependant variables (1) sites, (2) duration and (3) pages. Only the last two months of searches are used. Each table presents 3 separate regressions run for each of the impacted domains, aa.com, orbitz.com and expedia.com. Jan-May is an indicator for the five months January-May, Dispute is an indicator for the year of the dispute 2011, Focal is an indicator for the impacted domain $\boldsymbol{\beta_1^F}$ is the relevant treatment effect.

Table 27: Remove outliers

		aa.com		orbitz.com		expedia.com	
(1) sites							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.022	7.32	0.020	6.92	0.018	6.36
Jan-May X Dispute	β_1	-0.009	-1.92	-0.006	-1.21	-0.005	-1.09
Jan-May X Focal	β_0^F	-0.008	-1.13	0.027	3.12	0.066	5.50
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.026**	**2.27**	**-0.036**	**-2.20**	**-0.049**	**-2.47**
(2) durn							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.154	7.47	0.137	6.92	0.110	5.79
Jan-May X Dispute	β_1	-0.052	-1.49	-0.025	-0.73	-0.023	-0.70
Jan-May X Focal	β_0^F	-0.097	-1.69	0.190	3.23	0.646	8.03
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.193**	**2.02**	**-0.269**	**-2.94**	**-0.302**	**-2.28**
(3) pages							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.179	8.81	0.187	9.35	0.156	7.94
Jan-May X Dispute	β_1	-0.076	-2.16	-0.091	-2.59	-0.084	-2.42
Jan-May X Focal	β_0^F	0.248	3.84	0.121	2.16	0.642	9.37
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.181**	**-1.55**	**0.075**	**0.86**	**-0.049**	**-0.42**
N obs	4,354,193						
N id	82,762						
Fixed effects	id, year, year X focal						
Cluster	id						

Table 28: Searches on impacted domains, relative to competitors and pooled control period assuming the dispute lasted 3 months

		aa.com		orbitz.com		expedia.com	
(1) sites							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.026	7.98	0.024	7.76	0.021	6.97
Jan-May X Dispute	β_1	-0.005	-1.05	-0.003	-0.65	-0.002	-0.44
Jan-May X Focal	β_0^F	-0.012	-1.59	0.018	2.01	0.071	6.01
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**0.010**	**0.82**	**-0.028**	**-1.92**	**-0.047**	**-2.39**
(2) durn							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.199	7.06	0.186	6.84	0.151	5.76
Jan-May X Dispute	β_1	-0.064	-1.36	-0.053	-1.15	-0.047	-1.06
Jan-May X Focal	β_0^F	-0.020	-0.22	0.203	2.34	0.792	6.88
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.063**	**-0.42**	**-0.250**	**-1.98**	**-0.353**	**-1.88**
(3) pages							
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	β_0	0.221	8.51	0.239	9.12	0.212	8.28
Jan-May X Dispute	β_1	-0.082	-1.79	-0.125	-2.66	-0.126	-2.76
Jan-May X Focal	β_0^F	0.414	3.22	0.107	1.38	0.576	5.76
Jan-May X Dispute X Focal	$\boldsymbol{\beta_1^F}$	**-0.635**	**-2.90**	**0.105**	**0.91**	**0.118**	**0.72**
N obs	4,389,417						
N id	82,886						
Fixed effects	id, year, year X focal						
Cluster	id						

Table 29: Site visits for consumers living near airports with varying degrees of American presence: diff analysis

(1) No American Airlines serving nearby airports

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	-0.022	-0.69	0.160	1.42	0.318	1.34
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.010**	**0.13**	**-0.064**	**-0.44**	**-0.308**	**-1.22**
N obs	1,203						
N	469						

(2) American is most important airline in nearest airport

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.032	1.42	0.024	0.76	0.057	1.97
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**-0.016**	**-0.44**	**0.043**	**0.92**	**0.005**	**0.12**
N obs	60,899						
N	20,248						

(3) Airport is neither American-absent or American-important

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.012	1.31	0.071	6.56	0.119	6.47
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.026**	**1.67**	**-0.063**	**-3.11**	**-0.048**	**-1.65**
N obs	190,514						
N	60,788						

All data

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.017	1.89	0.056	5.12	0.100	6.51
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.016**	**1.1**	**-0.035**	**-1.91**	**-0.037**	**-1.52**
N obs	258,201						
N	82,886						

Note: This table presents a diff analysis for visits to the treated domains for three subsets of the data, 1) airports with No American presence, 2) Airports where American is the most important airline and 3) the rest. The hypothesis is that we will see the strongest effect of the dispute in susbet (3), because this is where the role of aggregators is most relevant. For reference, analysis using All data is also presented. $\boldsymbol{\delta_1}$ is the relevant treatment effect.

Table 30: Site visits for consumers living near airports with varying degrees of competition: diff analysis

High competition airports

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.123	1.99	0.074	0.76	0.102	1.43
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**-0.017**	**-0.21**	**-0.076**	**-0.68**	**-0.105**	**-0.98**
N obs	14,418						
N	4,110						

Low competition airports

		aa.com		orbitz.com		expedia.com	
		coeff	t-stat	coeff	t-stat	coeff	t-stat
Jan-May	δ_0	0.015	1.27	0.064	3.57	0.117	4.72
Jan-May X Dispute	$\boldsymbol{\delta_1}$	**0.036**	**1.4**	**-0.075**	**-3.04**	**-0.067**	**-1.67**
N obs	62,628						
N	19,312						